Lower Limb Analysis of the Biomechanical Gait Cycle at Various Phases in Real Time

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Abstract. Biotechnology is playing an extremely important part in medical advances. In actuality, they are the basis of pathology diagnosis, which provides doctors with the quantitative data required to choose the best treatment. This study looks at the facts of a case of weak muscular activity and devises solutions to help the disabled or very ill for the specialist to improve the patient's condition by choosing accurate treatment. This would enhance their psychological condition and make it easier for them to do their daily activities. The data are collected by surface electromyography (EMG) from the lower limb of the leg gait events (heel strike, foot flat, midstance, heel off, toe-off, and medium swing) on the right, left, and both legs are estimated. The system consists of a microcontroller, a myograph sensor, and Bluetooth. Healthy individuals utilize both legs regularly in a balanced manner and during a walk as well as stair ascending tests. On both sides of the legs (right and left), sensors are placed on the quadriceps, hamstrings, tibialis, and triceps muscles. The system was tested on 28 people (17 males and 11 females) aged 24–54 years old. The suggested method is used to analyze gait in real-time.

Keywords: bluetooth; gait cycle; hamstrings muscle; myograph sensor; microcontroller; quadriceps muscle; surface emg; tibialis muscle; triceps muscle.

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1 Introduction

Electromyography (EMG) is a method for measuring and monitoring electrical impulses in muscle contraction. An EMG examination can be used in a variety of clinical and biological circumstances. Surface EMG is employed in experimental gait analysis and for physiological diagnostics. EMG is applied to control prosthetic devices such as artificial limbs, forearms, arms, knees, and lower limbs. So, a systematic review of current publications on the EMG activity of six muscles throughout physical fitness activities in healthy individuals was proposed [1]. However, the level of proof in the included papers was mostly medium, suggesting that further high-quality research was needed to decrease the risk of distortion and make definite conclusions concerning muscle activation. Also, study of electromyography systems, control models, problems, and potential future approaches was introduced [2]. This review focuses on the potential for EMG control to enable expanded capabilities in mechanical lower limb prostheses as well as the challenges, knowledge gaps, and research possibilities in this area from the viewpoints of patient care and individual muscle control. In addition, to capture the mechanical behaviour of the lower leg, staircase ambulation was used [3] as a basis for wearable technology and control systems. This article would specifically address transitions between level walking and stair mobility, as well as transitions between bipedal walking and walking.

Biomedical technologies are becoming increasingly important in modern medicine. In reality, they were at the heart of pathology diagnosis and follow-up, providing doctors with the statistical data needed to choose the best medication. The biomedical techniques that are used in gait parameters, covering the top issues utilized in clinical practice for neurologic, musculoskeletal, and rheumatic disorders and emphasizing their usefulness in the clinical environment [4]. In addition, electrical impedance myography (EIM) is a bioimpedance method that records the voltage produced by delivering a low or high over a muscle area without triggering myofiber or neuronal nerve impulses. The volume conduction properties (VCPs) of the muscle were measured using EIM. VCPs have the potential to be used as a standardized, measurable, and reliable electrophysiological diagnostic of muscle [5]. A classification tree gait pattern identification model effectively detected loading response, push-off, and swing for five distinct environments as well as a variety of walking speeds, using input data from the leg and knee was proposed [6]. The classifier proved resistant to a variety of simulated travel scenarios encountered in daily life and was able to generalize previously unknown data from diverse participants. Furthermore, displaying muscle activation and strength utilizing an EMG with auditory, vision, and/or motion presentation has been accomplished [7]. However, employing conductive gel to link the EMG electrode to the skin surface would generate a steady signal of muscle activity

There are many areas, which can measure the muscle activity, and there are many researches in these fields such as to examine the worker's body position during lifting and to compare the use of lower back support while lifting. It also uses EMG to study the worker's muscle function during excessive lifting and CATIA Software to replicate the worker's movement for rapid upper limb assessment (RULA) findings. The results demonstrate that workers who use lower back support have raw EMG signals with lower muscle activity than workers who do not use lower back support. When compared to not using back support, utilizing belt support can lower muscular activity by up to 67.4% [8]. Similarly, development of low back discomfort (LBD) when standing was linked to spinal muscle activation and pelvic motion. In analysis, the system looked at whether age, gender, and long-term work habits modified the LBD. However, given the relatively minor changes discovered, the therapeutic significance of this discovery in the chosen difference requires further investigation [9]. Although, a surface electromyography (sEMG) electrodes were used to measure muscle activity in the bilateral and trapezius muscles during the continuous farmland preparation procedure. Objective preference findings suggest that the bilateral, tracked by the trapezius left muscle, were the most uncomfortable during earthwork [10]. Based on machine learning, a unique approach for classifying gait phases in power gait exoskeleton users was proposed [11]. A period camera mounted on the crutches used for assisted walking was employed to capture the depth information. The machine learning approach predicts the first stage of data collection and processing throughout which the 3D points related to the foot and those related to the surface are established.

On the other hand, there are many research measured the muscle activity for arm, forearm, upper arm, and wrist as well as arm like an electrical device that can estimate the activity of any muscle in the human body was generate. The contraction in the normal case, with athletic body muscles, as well as in the situation of neuromuscular disorder was designed [12]. The initial concept was based on a biosensor on the biceps muscle. Muscle activity was monitored using different hand-loaded weights and varied ranges of action of the elbow joint. In addition, a surface EMG signal based joint torque estimate technique was provided to quantify the motion intention. To improve the accuracy of the calculated torque, a neural network was employed to learn the ideal factor of muscular strength. However, it should focus on creating a control technique based on this torque estimation method to operate rehabilitative exoskeleton robots [13]. Moreover, examines the effectiveness of stroke survivors in terms of detecting weak muscle activity and reaction by involuntary amplitude variation of EMG signals was illustrated. Using surface EMG data obtained from six hemiparesis stroke patients and six healthy participants, according to the findings, the amplitude-independent algorithm performed better in terms of recognizing weaker muscle activity and avoiding false alarms. However, this may be done by utilizing surface EMG data from individuals with various kinds of damage to validate the effectiveness of amplitude-independent approaches for detecting muscle activation [14]. Besides, a compare EMG for handstands done on three different pieces of equipment (ground, circles, and parallel bars), as well as the variation between juvenile and highly-trained senior gymnasts was presented. The study included ten adults and fifteen young gymnasts. Researchers looked at the magnitude of EMG signals in thirteen muscles that were standardized by the arbitrary angle of maximal exercise voluntary movement [15].

A new force myography (FMG) sensor has been developed to identify physical muscle contractions in lost limbs [16]. FMG is an approach for registering limb muscle activity utilizing accelerometer sensors and movement observation applications. Notwithstanding its recent recognition among investigators, many of its essential properties are right now unclear. The FMG consists of one or maybe more sensors for obtaining muscle contraction data from missing limbs and an embedded system that receives input data from the sensors as well as produces control instructions. Also, techniques for converting FMG signals from the sensing element to control instructions have been developed. Moreover, a muscular activity visualization system was developed to investigate the mapping link between hand gestures and activated upper arm-specific muscles. The graphics system's human-computer interaction showed that this approach could visually depict the relationship between multiple channels in the image space, allowing users to intuitively recognize the activity intensity of different muscles in hand movements [17]. To determine the lowest sample frequency required for capturing upper-limb FMG responses without compromising signal quality. Twelve participants took part in the test in which they were taught to perform quick hand motions while

FMG responses from the wrist and the bulk area of the arm were monitored [18].

In the same way, a muscle activity for the lower limbs and knee is clarified like postural control, as well as trunk independence, increased considerably after multi-muscle stimulation of the lower limbs was proposed. The aforementioned lower body part multi-muscle stimulator training strategy, using standard parameters at sub-maximal rates, is therefore expected to benefit trunk functional status. To test the generalizability of the findings and the motor patterns in assisted stepping, the number of musculoskeletal electrical events, stand training routines, and a larger sample size of studies were required [19]. Along with, to examine the effects of hippotherapy on lower-body activation and gross motor performance in participants with cerebral palsy in a population with appropriate motor development. It is possible to infer that hippotherapy offered a sequence of muscular stimulation that resulted in gains in capability and lower limb activation, and this treatment practice could contribute to the active recovery and better motor ability of people with cerebral palsy [20]. Four short pieces of training of submaximal attempt in eccentric (ECC) cycling resulted in lower activities of the rectus femoris (RF), biceps femoris (BF), soleus (SOL), and vastus lateralis (VL) muscles. Also, an impression of mostly less effort in ECC than in Concentric (CON) cycling across a variety of power outputs – despite the fact that most different factors were not different between exercise methodologies prior to the event. Subdivisions in muscular activity and heart rate decreased following the cycling events but were generally larger with ECC cycling. However, before doing any muscular activity or sensory tests, future studies should consider undertaking numerous periods of ECC cycling [21]. In spite of, to examine hip and knee muscular activation during single-limb standing and single-limb squat in men having patellofemoral pain (PFP) as well as a control group, which thus did not have PFP was proposed. Furthermore, muscle activation patterns differed between the PFP and healthy individuals. As a result, the findings confirm the idea that any impairment in the intermediate muscles involved in the leg might have an impact on the patellofemoral joint [22].

Inertial motion detectors are essential components of today's intelligent devices. They have the ability to be a component of future technologies like intelligent buildings, the internet of things (IoT), and the internet of everything (IoE). A two-stage sensor fusion technique that produces joint angle in real-time was proposed, implemented, and verified [23]. In the first stage, the drifts in each inertial sensor combined gyroscope data were estimated using the method designated gradient declivity. To provide a real-time evaluation of the angular position, the inclination data from both inertial sensors were combined in the second stage using a gradient declivity approach. Examines and develops a mobile gait detection method for patients depending on an inertial measurement unit, including the hardware and software design of the data collection module, were presented [24]. Control performance of the musculoskeletal systems is used to determine gait kinematics and reaction mechanisms [25]. Inertial sensor information proposes a methodology for immediately estimating gait from inertial sensors using a single dynamic algorithm. Furthermore, the muscular effort was reduced to ensure a one-of-a-kind response. A seven-inertial measurement was used to collect data from 10 people walking and jogging at six different speeds. Create practical and reliable approaches for detecting gait movements in people with gait abnormalities in real-time. In addition, a collection of methods for online identification of gait patterns and actions was presented. Furthermore, they created an upgraded version of an IMU-based portable device that enables gait data monitoring and recording [26].

Typical gait analysis approaches were carried out under controlled conditions in a costly motion-capture laboratory. Although the technique produces reliable findings, it does not allow for continual monitoring and evaluation. Wearable systems with inertial measurement units are an option. However, inertial sensor suffers from drift as a result of the double processing used to obtain position information. However, ultrasonic sensors can be used to counteract this drift. A simple, reliable measure of the ankle angle (AA) utilizing ultrasonic sensors and triangulation methods without using sophisticated inertial sensor techniques was proposed [27]. Furthermore, the suggested technique detects the minimal toe clearance (MTC), which was another significant gait parameter. The suggested system analyzes a person's gait for long durations for a day scenario and assesses essential gait characteristics that were utilized for gait problem therapy and fall detection in the older adult population. Finally, a novel approach for measuring knee joint angle was proposed. The technique used force myogram responses from thigh muscles as individuals walked on a machine at various speeds, including slow, moderate, high, and run. The method has been validated on both able-bodied people and a transfemoral prosthesis. However, research might look at expanding the current technique to a more diverse patient group [28]. The actions of the multifidus, internal oblique, quadriceps, and tibialis anterior muscles in inactive adults were identical to those observed with walking and hippotherapy employing various methods and elements. The results of this controlled research may be compared to those of patients with various clinical illnesses who appear to have independent walking impairment in order to truly comprehend the alterations that happen in their trunks [29].

The drawback from the previous works is that they have used only one sensor location and one to five muscle types, so to get effective results in collecting data and analyzing it, this paper uses heel-strike, foot flat, midstance, heel-off, toe-off, and medium swing of the right leg, left leg, and both legs. This paper has been classified several related studies based on sensor location, sensor type, muscle test, and gender and compared with proposed method as illustrated in (Table 1).

The purpose of this study is to get a more thorough understanding of the challenges posed by weak muscular activity and to propose options to assist the disabled by enabling the specialist to assist patients, improve their situation and stimulate the weak muscles. The aforementioned would improve their psychological state and enable them to do their everyday tasks more naturally. The system components include a Bluetooth module, a myograph sensor, and a microcontroller. It was established during a walking and stair climbing test that healthy participants use both legs equally and in a balanced way.

The research contributes:

1. A review of the use of muscle activity systems in previous works.
2. To collect surface EMG data from the lower limb of the leg.
3. To predict gait events (heel-strike, foot flat, midstance, heel off, toe-off, and Medium swing) of the right leg, left leg, and both legs.

2 Methodology

The suggested system consists of a myograph put on the limb of the user, the data (muscle activity) is wirelessly transmissible to a computer or phone for analysis, and a microcontroller processes the data. The sensors were placed on the legs of the chosen muscles, namely quadriceps, hamstrings, tibialis, and triceps on both sides (right and left). The suggested method can be used for real-time motion analysis. The system is simple to wear, practical for outdoor usage, lightweight, and commercially feasible. Fig. 1 represents the block diagram of the system with all components.

Table 1 Comparison of sensor location, sensor type, muscle test, and gender in previous works.

Year, Ref.	Sensor location	Sensor type	Muscle test	Gender
2020, [8]	back	myograph	low back	7 male
2020, [12]	arm	myograph	biceps	4 persons
2021, [13]	arm	myograph	elbow joint angle	not available
2020, [14]	arm	myograph	not available	6 healthy and 6 hand impairment (4 female)
2019, [19]	lower limbs	myograph		
2019, [9]	back	myograph	erector spinae and medio-lateral pelvic	15 young females, 15 young males, 15 older males, and 15 young males
2019, [20]	lower limbs	myograph		7 individuals
2019, [22]	hip and knee muscles	myograph	not available	18 males
2020, [16]	forearm	force myography sensor	forearm	1 male
2020, [17]	arm	sEMG	upper arm muscle	not available
2019, [15]	arm	EMG	anterior deltoid, pectoralis major, latissimus dorsi, biceps brachii, and trapezius descendent muscles	10 adult and 15 young
2021, [10]	bellies	sEMG	trapezius and biceps brachii	10 volunteers
2019, [18]	wrist and forearm	force myography (FMG)	not available	12 volunteers
2020, [28]	knee	FMG	thigh muscles	8 men
Proposed method	lower limbs	myograph	quadriceps, hamstrings, tibialis, and triceps on both sides (right and left).	28 persons (17 males and 11 females)

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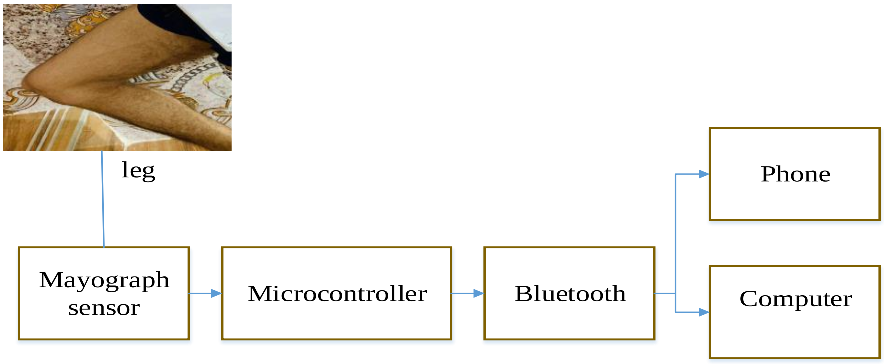

Fig. 1 Block diagram of the system.

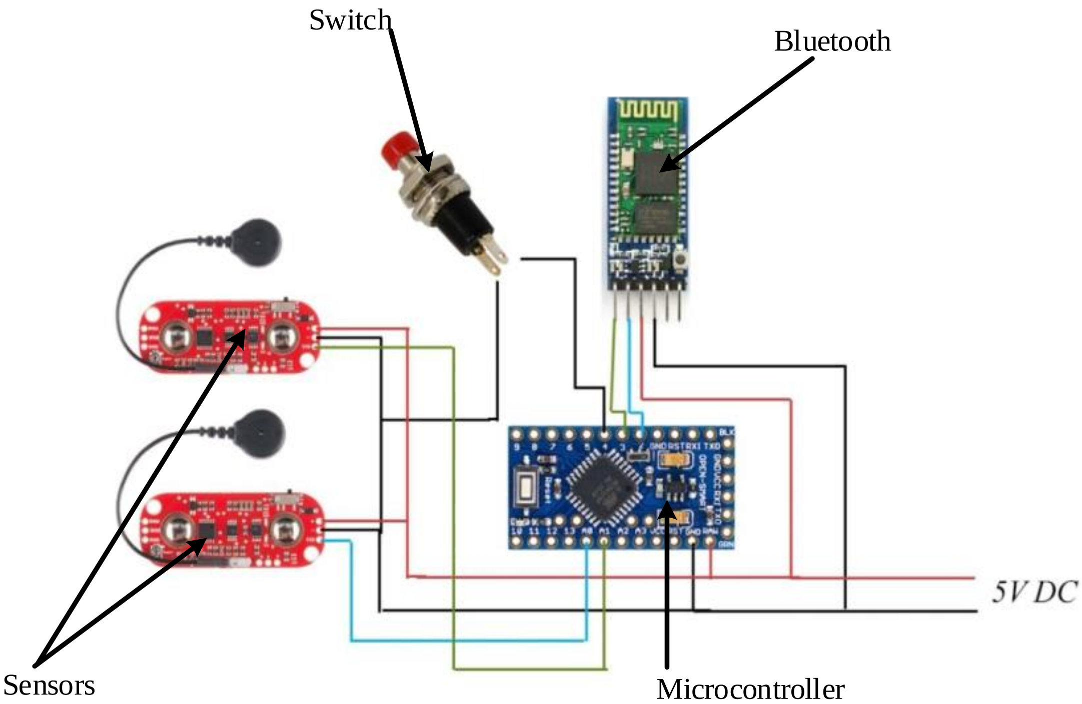

Fig. 2 Schematic and the hardware components of the system.

Table 2 Action of muscles during activities.

Muscle name	Action	Ph. 1	Ph. 2	Ph. 3	Ph. 4	Ph. 5	Ph. 6
Quadriceps	knee extensors helping in control of knee flexion	W.	W.	N.W.	W.	N.W.	N.W.
Gluteus Maximus	Move of the hip and thigh	W.	W.	N.W.	N.W.	N.W.	N.W.
Hamstrings	Extend the hip and flex knee via concentric contraction	W.	N.W.	N.W.	N.W.	N.W.	W.
Iliopsoas	hip flexor and active during the initial and mid-swing phase	N.W.	N.W.	N.W.	W.	W.	N.W.
Tibialis Anterio	During loading response and initial swing and the ankle dorsiflexion during the late swing phase.	W.	W.	N.W.	W.	W.	W.
Triceps	During late mid-stance and terminal stance	N.W.	N.W.	W.	N.W.	N.W.	N.W.

Ph.: phase, W.: work, N.W.: not work,
Ph. 1: heel strike, Ph. 2: foot flat, Ph. 3: Midstance, Ph. 4: Heel off, Ph. 5: Toe release, Ph. 6: Medium swing.

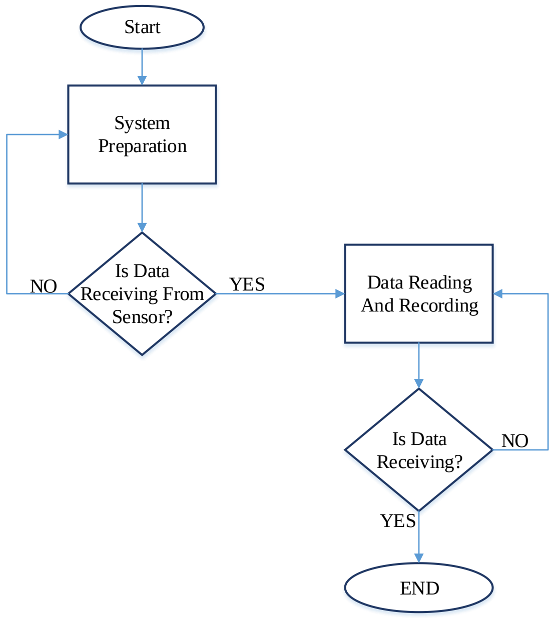

Fig. 3 System flowchart.

Besides, Fig. 2 illustrate the schematic and the hardware components of the system, which comprises an Arduino Pro Mini board [30, 31], two MyoWare muscle sensor module [32], and Bluetooth [33, 34]. The signals from the MyoWare are received by the microcontroller, and the computer or phone serves as an adapter between the microcontroller and the MyoWare. In the Arduino programming, the obtained signals are processed using a specified algorithm that cleared as a flowchart which is depicted in Fig. 3.

3 Data Collection

The position and origin point of the muscles themselves determine the individual body parts responses to a muscle function. To make this procedure simpler, the system will concentrate on the body's skeletal muscles. The mobility of the majority of skeletal muscles is restricted or guided by their attachment to bone, cartilage, or connective tissue. The testing of the data is applied to 28 normal people (17 males and 11 females) aged from 24 to 54 years old. The data for this work has been collected from following:

Part 1: for normal walking with and without weight (5 kg, 10 kg, and 15 kg); for quadriceps as well as hamstring muscles, once for left leg and once for right leg with six phases.

Part 2: for stair clamping with and without weight (5 kg, 10 kg, and 15 kg), for quadriceps as well as hamstring muscles, once for the left leg and once for the right leg, with six phases.

Part 3: six phases for two legs at the same time for normal walking and stair clamping with and without weight (5 kg, 10 kg, and 15 kg) for quadriceps and hamstring muscles.

Part 4: for normal walking with and without weight (5 kg, 10 kg, and 15 kg); for Tibialis and triceps muscles, with six phases, once for left leg and once for right leg.

Part5: for stair clamping with and without weight (5 kg, 10 kg, and 15 kg), for tibialis as well as triceps muscles, once for the left leg and once for the right leg, with six phases.

Part 6: six phases for two legs at the same time for normal walking and stair clamping with and without weight (5 kg, 10 kg, and 15 kg) for Tibialis and triceps muscles.

4 Result and Discussion

For muscle evaluation by observing the user and recording the readings of muscle contraction and relaxation during walking and climbing the stairs for all the parts that were mentioned in the collection of data, it is notice that some muscles strengthen and weaken during the phase that is assigned to them. As illustrated in Table 2, that shows the action of muscles during activities.

The collected data presented in Table 3 represented the quadriceps and hamstring muscles and the sensor on the left leg (with or without weight). The numbers in the tables are the activity of the muscles as a voltage that was collected from the sensor, which is measured in microvolts, and Fig. 4 shows the phases for each case.

The collected data presented in Table 4 represented the quadriceps and hamstring muscles and the sensor on the left leg (with or without weight). The numbers in the tables are the activity of the muscles as a voltage that was collected from the sensor, which is measured in microvolts, and Fig. 5 shows the phases for each case.

The collected data presented in Table 5 represented the tibialis and triceps muscles and the sensor on the left leg (with or without weight). The numbers in the tables are the activity of the muscles as a voltage that was collected from the sensor, which is measured in microvolts, and Fig. 6 shows the phases for each case.

Table 3 Activity of the quadriceps and hamstring muscles in microvolts (with or without weight).

Muscle name	Heel strike	Foot flat	Midstance	Heel release	Toe release	Medium swing
Gait cycle with normal walk						
Quadriceps	251	212	198	279	328	231
Hamstrings	92	70	56	91	88	57
Normal walk with 5 kg in the left hand						
Quadriceps	88	152	244	221	243	191
Hamstrings	66	171	234	342	355	244
Normal walk with 10 kg left hand						
Quadriceps	297	236	145	163	255	205
Hamstrings	73	87	87	26	65	60
Normal walk with 15 kg left hand						
Quadriceps	317	329	300	314	334	330
Hamstrings	499	455	416	433	412	366
Normal walk with 5 kg in the right hand						
Quadriceps	323	327	322	312	355	368
Hamstrings	315	312	300	307	355	352
Normal walk with 10 kg right hand						
Quadriceps	362	312	308	323	330	333
Hamstrings	448	318	308	397	319	324
Normal walk with 15 kg right hand						
Quadriceps	170	178	129	186	215	134
Hamstrings	174	192	132	152	150	139

a b c

d e

Fig. 4 Phases of a) heel strike phase, b) foot flat phase, c) midstance phase, d) heel off phase, e) medium swing phase.

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Table 4 Activity of the quadriceps and hamstring muscles in microvolts (with or without weight).

Muscle name	Heel strike	Foot flat	Midstance	Heel release	Toe release	Medium swing
Stair climbing						
Quadriceps	116	224	214	128	146	139
Hamstrings	227	325	238	231	265	390
Stair climbing with 5kg in the left hand						
Quadriceps	195	213	215	171	214	153
Hamstrings	255	291	282	263	253	276
Stair climbing with 10kg left hand						
Quadriceps	151	212	165	191	245	303
Hamstrings	256	281	216	254	291	250
Stair climbing walk with 15kg left hand						
Quadriceps	128	219	231	280	192	244
Hamstrings	312	236	314	285	218	234
Stair climbing with 5kg in the right hand						
Quadriceps	125	237	195	324	142	205
Hamstrings	157	218	253	112	214	176
Stair climbing with 10kg right hand						
Quadriceps	163	512	378	114	221	251
Hamstrings	193	318	200	134	161	250
Stair climbing walk with 15kg right hand						
Quadriceps	192	352	590	408	400	619
Hamstrings	183	272	380	357	215	305

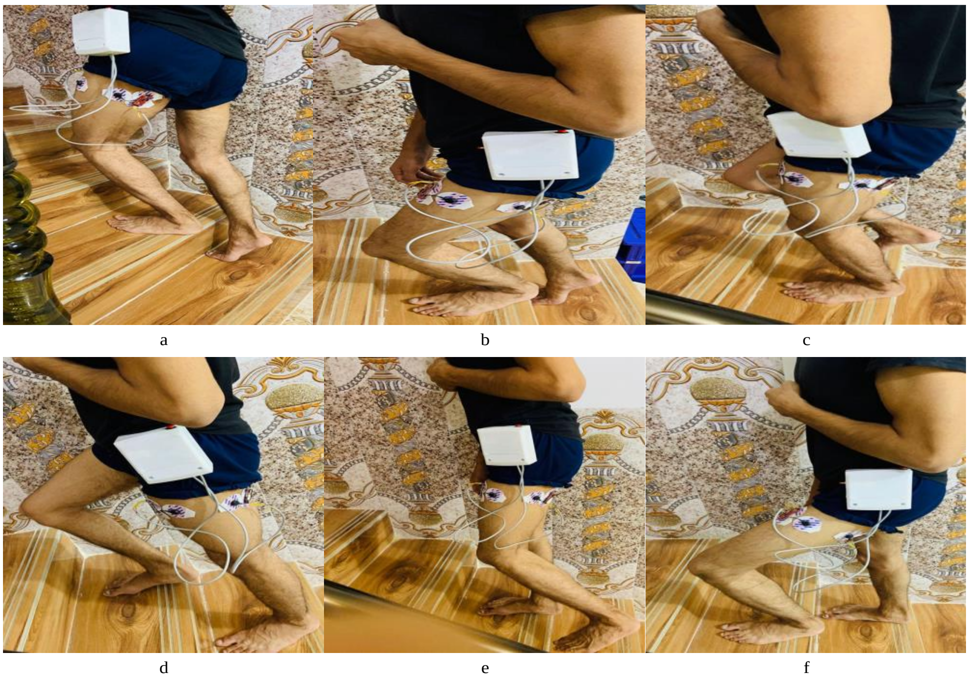
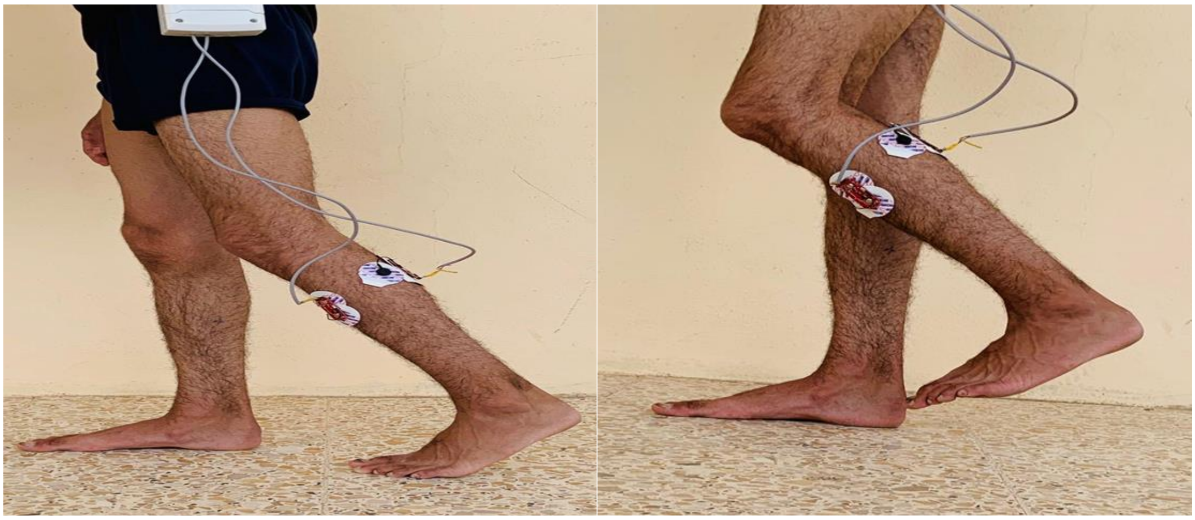


Fig. 5 Phases of a) foot flat phase, b) toe release phase, c) medium swing phase, d) midstance phase, e) midstance phase, f) heel strike phase.

Table 5 Activity of the tibialis and triceps muscles in microvolts (with or without weight).

Muscle name	Heel strike	Foot flat	Midstance	Heel release	Toe release	Medium swing
Stair climbing						
Tibialis	121	221	349	135	128	166
Triceps	94	124	149	121	139	96
Stair climbing with 5 kg in the left hand						
Tibialis	74	225	357	169	134	186
Triceps	98	130	176	132	175	114
Stair climbing with 10 kg left hand						
Tibialis	212	214	394	124	169	102
Triceps	105	102	174	175	168	87
Stair climbing walk with 15kg left hand						
Tibialis	137	246	225	235	195	285
Triceps	114	113	224	318	405	163
Stair climbing with 5kg in the right hand						
Tibialis	266	272	379	228	199	168
Triceps	120	147	173	182	291	158
Stair climbing with 10kg right hand						
Tibialis	121	276	527	287	282	202
Triceps	106	147	183	126	389	246
Stair climbing walk with 15kg right hand						
Tibialis	145	445	286	338	214	209
Triceps	109	122	195	210	187	124



a b

Fig. 6 Phases of a) foot flat phase, b) medium swing phase.

The collected data presented in Table 6 represented the right (R.) triceps and left (L.) triceps muscles and the sensor on the left and right leg (with or without weight). The numbers in the tables are the activity of the muscles as a voltage that was collected from the sensor, which is measured in microvolts, and Fig. 7 shows the phases for each case.

Table 6 Activity of the right (R.) triceps and left (L.) triceps muscles in microvolts (with or without weight).

Muscle name	Heel strike	Foot flat	Midstance	Heel release	Toe release	Medium swing
Normal walk						
R. Triceps	138	141	193	124	120	117
L. Triceps	130	124	127	103	200	190
Normal walk with 5kg in the left hand						
R. Triceps	85	202	145	76	162	188
L. Triceps	167	111	103	105	231	193
Normal walk with 10kg left hand						
R. Triceps	124	80	177	70	160	190
L. Triceps	118	140	121	155	181	204
Normal walk with 15kg left hand						
R. Triceps	88	374	356	98	213	188
L. Triceps	125	160	109	100	165	211
Normal walk with 5kg in the right hand						
R. Triceps	92	208	292	100	122	128
L. Triceps	128	193	124	105	212	231
Normal walk with 10kg right hand						
R. Triceps	106	190	324	80	79	115
L. Triceps	130	163	146	107	228	282
Normal walk with 15kg right hand						
R. Triceps	167	140	355	86	135	127
L. Triceps	110	240	110	100	244	258

a b

Fig. 7 Phases of a) heel strike phase, b) Midstance phase.

From the results, in normal walking with quadriceps muscles, when the weight is in the left hand, the activity increases, and in stair climbing, when the weight is in the left hand, the activity decreases significantly in the first three stages and increases in the other three. Also, in normal walking with tibialis muscle weight in the left hand, the activity increases, and when stair ascending with weight in the left hand, the action is the same as with weight. In addition, in a comparison between the left and right triceps muscles, when the weight is in the left hand, the activity increases in the left muscle more than the right, and when the weight is in the right hand, the activity increases in the right muscle more than the left.

5 Conclusion

In this paper, the activation values of the tibialis, triceps, quadriceps, and hamstring muscles are measured and analyzed in different conditions. The value is found by a wireless system using an Arduino microcontroller and wearable muscle sensors. With the practical experience, which involved the gait cycle at various phases, the biomechanics influence was implemented. On the right, left, and both legs, gait cycles are computed in real-time for heel contact, foot neutrality, oriented practices, heel release, toe-off, and medium swing. The results are found with phases of the gait cycle in normal walking and upstairs, with and without lifting weight. The measurements are applied to 28 individuals (17 males and 11 females) aged 24–54 years old, and the collected data represents the voltage activity of the muscles that can be used for future work to get more equate results to analyze the biomechanical gait cycle at various phases in real time.

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