Artificial Neural Network for Sit-to-Stand classification based on Inertial Measurement Units Data

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***Abstract*— According to some statistics published by Centers for Disease Control and Prevention (CDC), 1 in 50 people approximately around the world is incapable of achieving some of daily's life activities by his own due to paralysis. Paralysis is the partial or total inability of the human body to perform some movements caused by stroke, spinal cord injury, multiple sclerosis, birth defect, etc. Today, number of paralysis "victims" is increasing dramatically making over 6 million people paralyzed around the world, with some cases were the physical therapy becomes unable to heal.**

Consequently, Technology has constantly been a major player in a large number of physical therapy applications, and offers many advantages for paralyzed people that the physical therapy is not able to provide. Recently, exoskeleton patient motion aiding technology was introduced in order to supply disabled people and regain mobility.

The main goal of this project is to study the Sit-to-Stand and Stand-to-Sit transfer in 10 young healthy subjects. IMU (Inertial Measurement Unit) wearable sensors, more specifically MPU6050 sensors, are used in the performed experiences in order to extract desired raw data such as the acceleration, angular rate and inclination of lower limb different segments including metatarsal, shank and thigh segments and the inclination of the trunk. Thus, ankle, knee and hip joints angles were derived.

Furthermore, extracted features are studied, analyzed and used to establish epochs and recognize phases of the Sit-to-Stand gesture based on a number of previous Sit-to-Stand literature of art. This is accomplished using Artificial Neural Network, using different architectures and choosing the best one, which resulted in four main phases: flexion phase, transfer phase, extension phase and stabilization phase.

Finally, and using the proper Neural Network with the higher accuracy (92.3% accuracy using the 30 layers architecture), a Sit-to-Stand algorithm is proposed and modeled.

Keywords*— *Artificial Neural Network, Sit-To-Stand algorithm, Gait analysis, Classification, IMU sensors

I. Introduction

Gait and Sit To Stand (STS) analysis are studies based on different techniques using various devices and sensors able to capture some human motions and extract the corresponding parameters and data for further applications. Usually, three common techniques are used: Image Processing, floor Force Sensors and Wearable Sensors.

Image processing technique is performed in a special laboratory equipped with a set of cameras, either analog or digital ones. Extracting gait and STS parameters using this method can be done by taking several images during the experience, processing, feature extraction and classification. [1].

As its name indicates, floor force sensors technique uses a set of force platforms which enable the user to extract and calculate pressure, force or pressure and force based data when the subject perform gait or STS tasks on the sensors. This technique [2], like the previous one, needs special equiped high end laboratories. Wearable sensors is a new technique that provides great results and same accuracy as image processing and floor force system, and overcomes these methods by the fact that it is less complex, since it doesn't require special environment and can be performed in-lab, less time consuming and less costly. [3] During a STS or gait study, the participant has a number of sensors positioned on his body, usually segments and joints, in order to extract desired data. [3]

Tay et al. study was founded on Newton's.motion.law. Since fair forces applied on the human body are pro rata to the acceleration of the latter, Tay et al introduced a method by integrating two accelerometer sensors, positioned on the left and right ankles of a subject to stalk walking, and an accelerometer near the cervical vertebra in order to supervise different body positions during the task. [4]

Likewise, they were capable of evaluating some interesting parameters like peak acceleration and time during a sitting and standing tasks.

Inspired from Android Phone Sphere application allowing to estimate the direction of rotating the smartphone, Kai-Yu Tong & Granat studied gait and STS movements by placing 1-axis gyroscopes on the shank and thigh of each subject in order to extract every segment velocity rate. They conclude the efficiency of this method in order to derive other parameters such as inclination, orientation and number of movements. [5]

Our experience and study were basically based on Tadano et al. [6]. They proposed a three dimension gait analysis using wearable, combination of 3-axis accelerometer and 3-axis gyroscope, sensors positioned on lower limb segments. Acceleration and angular velocity data were recorded, in real time, during walking task.

The direction and orientation, respectively to the gravitational force, were extracted from the accelerometer sensors in order to compute original positions, while various displacements and angular velocities were recorded using the gyroscope sensors.

Tadano et al. conclude that IMU based method showed accurate and validate results, comparatively to other common techniques, of quantitative data and parameters like segments acceleration, inclination and angular displacement.

Our suggested methodology in this paper will be described as follow : first, 50 STS tasks will be experimented on 10 subjects. The subjects have been asked to perform 5 trials, while 7 IMU sensors are placed on lower limb segments and the trunk. During the task, acceleration, angular velocity and inclination of lower limb segments and inclination of the trunk are recorded, using Arduino software, displayed on graphs, using MATLAB software, and interpreted. Joints angles will be derived and calculated. All these data are then classified using Artificial Neural Netowork, ANN, using various architectures. Afterwards, Receiver Operating Characteristic, ROC and confusion matrixes results of the most ideal ANN architecture are analyzed. Finally, all results will be used in order to suggest a STS conceptual model algorithm.

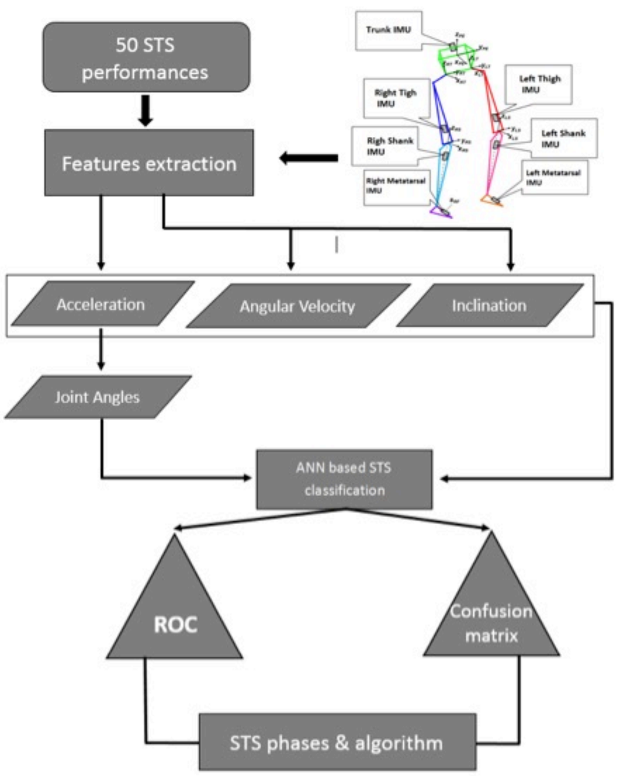

Figure 1- Flowchart Methodology

II. Materials and Methods

A. Inertial Moment Unit Sensors

Motion Processing Unit 6050 (MPU-6050), a part of IMU-6000 family, consists of a micro-electromechanical system, providing a 3 Degrees of Freedom of acceleration and 3 Degrees of Freedom of angular velocities values, using respectively a 3-axis accelerometer and a 3-axis gyroscope. It provides 6 Degrees of Freedom as a final result. This low priced sensor consumes less power and has a great performance comparatively to other IMU sensors. MPU-6050 sensors are compatible with Arduino and Raspberry pi boards and softwares using I2C and Serial Peripheral Interface (SPI) protocols.

B. Experimentations

10 healthy men participated in this experience, all these participants are between 20 and 25 years (Mean= 23 years, SD= 1.84), heights between 169 cm and 182 cm (Mean= 175 cm, SD= 4.7) and weights between 85 Kg and 99 Kg (Mean= 91.8 Kg, SD =3.89).

All participants are free of any orthopedic or arthritic disorder, and thus were all-able to perform the sit-to-stand independently without any human support or device assistance (e.g. knee support).

Participants were requested to sit on an armless chair with no active role of their arms in the sit-to-stand task. In order to maintain the vertical position of the trunk, each subject uses the back support of the chair, and his knees flexed to approximately 90^{o} with a space of 20 cm between his feet while placed on the ground.

Every participant was asked to perform 5 sit-to-stand-to-sit trials for 13 to 14 seconds after verbal signals.

TABLE I. EXPERIENCE PROCESS

Phase	Recording time
Sitting position	3 seconds
Transition phase (sit-to-stand)	2 seconds
Standing position	3 seconds
Transition phase (stand-to-sit)	2 seconds
Sitting position	3 seconds

Instrumentation consists of 7 IMU sensors (MPU 6050), Arduino software and armless back supported seats.

Sensors were positioned on 2/3 of each segment length (metatarsal, shank and thigh) of the left and the right parts, and 1 IMU is placed on the T3 thoracic vertebrae of the trunk illustrated in Fig.2 and Fig.3.

In this study, segments acceleration values, acquired from the accelerometer and segments angular velocity

values, acquired from the gyroscope, were collected simultaneously, displayed on the serial monitor of Arduino software and saved in a .txt format file.
Hip, knee and ankle angles were calculated from the acceleration values. The right placement of the IMU sensors is crucial to features extraction, because each sensor will indicate to a certain list of variables all obtaining to one parameter.
Each sensor will be coded to one parameter as illustrated in table II.

The angles calculation is shown in the following formulas:

$$p = arctan\left(\frac{Ax}{\sqrt{(Ay)^2 + (Az)^2}}\right)$$

$$\Phi = arctan\left(\frac{Ay}{\sqrt{(Ax)^2 + (Az)^2}}\right)$$

$$\Theta = arctan\left(\frac{\sqrt{(Ax)^2 + (Ay)^2}}{Az}\right)$$

TABLE II. SENSORS PLACEMENT

Sensor	Place
S1	Trunk
S2	Right thigh
S3	Left thigh
S4	Right shank
S5	Left shank
S6	Right metatarsal
S7	left metatarsal

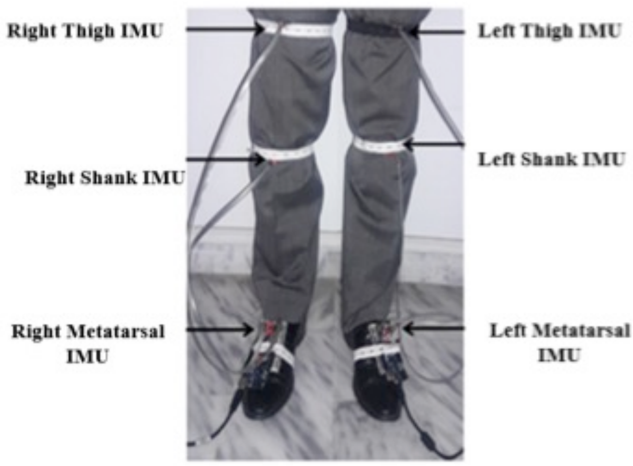

Figure 2- IMU sensors placement

Figure 3- Trunk IMU sensor Placement

C. Proposed protocol

In the first place, the subject is in a sitting position with feet positioned on the ground.

- Trunk, maintained in a nearly vertical position, and thigh, maintained in a nearly horizontal position relatively to the ground, forms a hip angle of 95 ^{o}.
- Shank, maintained in a nearly vertical position relatively to the ground, forms with the thigh a knee angle of 85 ^{o}.
- Metatarsal, maintained in a nearly horizontal position relatively to the ground, forms with the shank an ankle angle in a range of 85 ^{o}.

The first step, flexion phase, is demarcated by the movement of the subject's upper body part, especially the trunk, while lower body segments are immobile. The main base support in this phase is the seat or the chair.

So it starts from the sitting position and end when the trunk is flexed before lifting off from the seat or initial position.

- Knee and ankle joints angles remain the same while the trunk is flexed in a forward position resulting in a decrease of the hip joint angle of 35^{o} to achieve a flexion position of 60 ^{o}.
- Thigh, shank and metatarsal segments accelerations remain the same.
- Thigh, shank and metatarsal segments angular velocity remain the same

The second step, extension phase is differentiated from the first one from by several mechanical points. It is completed when maximum forward flexed posture is reached. A "transfer" of the base support occurs: the subject passes from the seat support to the feet support. The lower body movement accompanies the upper body movement.

This step begins when the subject starts to lift off from the seat and ends before starting the extension motion of different joints.

The third step, extension phase, also mechanically differs from the first and the second phase. We can simply say that the extension phase is the translation of the body in a vertical direction.

The Stabilization phase represents the final stage of a STS transfer.

Hip and knee angles of 170^{o} allow us to conclude that metatarsal and shank segment are nearly orthogonal, while shank, thigh and trunk are approximately aligned in a

vertical direction nearly perpendicular to the horizontal direction of the ground.
The different STS phases are illustrated in Fig.4.

Figure 4- STS Phases algorithm

Sit-to-Stand phases will be named respectively class 1, class 2, class 3 and class 4.

D. Features Extraction

All extracted features were recorded using Arduino software. Here is a table that displays each feature number and name.

TABLE III. FEATURES EXTRACTION

Feature Number	Feature Name
F.E.1	Trunk angles
F.E.2	Thigh Angles
F.E.3	Thigh Angular Velocity
F.E.4	Thigh Acceleration
F.E.5	Shank Angles
F.E.6	Shank Angular Velocity
F.E.7	Shank Acceleration
F.E.8	Metatarsal Angles
F.E.9	Metatarsal Angular Velocity
F.E.10	Metatarsal Acceleration

Each experience is made for 13 seconds approximately; each sensor can sense a value at 0.2 seconds. Thus for each feature status above we will have, a certain number of values that will be noted N, where N = 65 values. However, the total amount of values obtained at each experience that will be noted X, is equal to the N x Number of features = 10 x 65 = 650. To add, each experience is repeated 5 times, to get the most accurate values possible. Total Amount of Values (for each subject) , knowing that the experiment has been repeated 5 times is equal to 3250 values. For the 10 subjects, the total Amount of Values (for all subject) is equal to 32500 values.

In general, when two bones are re-joined, a joint is developed. The joint movement is completed by the presence of muscles. Since we are interested in the lower body parts and the trunk to study the Sit-to-Stand task, it is fundamental to use some anatomical terms related to different joints movement:
-Flexion: causes two parts or segments to get closer, decreasing the separating angle between them. It is usually used to describe a flexion movement of the hip and knee joints.
-Extension: causes two parts or segments to separate, increasing the separating angle between them. It is usually used to describe the extension movement of the hip and knee joints.
-Dorsiflexion: is the flexion of the ankle joint
-Plantar flexion: is the extension of the ankle joint.

Fig. 5 represents an ankle joint, formed by the metatarsal and the shank segments, with M and S the angles of respectively metatarsal and shank segments, while M' is the internal alternate angle of the S relatively to the ground. M is measured from the IMU sensor of the metatarsal segment, and thus M' is concluded from this sensor. S is measured from the IMU sensor of the trunk segment. Ankle angle can be seen on the figure as the sum of M' and S angles.

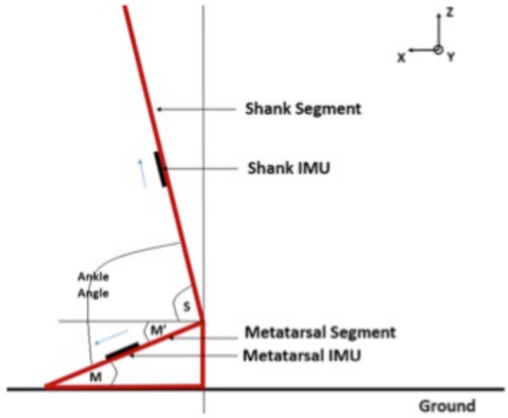

Figure 5- Ankle joint extraction

Same studies have been done for the knee joint, the hip angle. We only limited the calculation on the X-plan, since flexion and extension are only performed in the lateral plan.

E. Processing workflow

Extracted features have been fed into an artificial neural network. Fig.6 illustrated the general workflow.

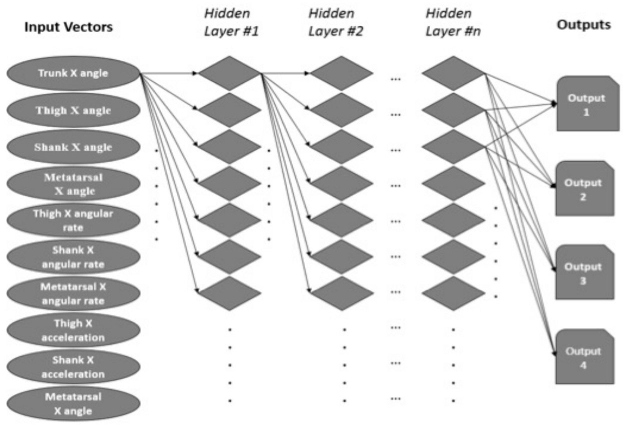

Figure 6- General workflow

After extracting features from MATLAB workspace, 32 480 data were introduced as input vectors to the ANN. In this statistical analysis, 10 samples were tested. The set of variables could be resumed as follow : X-axis metatarsal angles, X-axis shank angles, X-axis thigh angles, X-axis trunk angles, X-axis metatarsal angular velocity, X-axis shank angular velocity, X-axis thigh angular velocity, X-axis metatarsal acceleration, X-axis shank acceleration, X-axis thigh acceleration. Several neural network architectures were employed in order to find the most appropriate one using 5, 10, 15, 20, 25, 30 and 35 neurons per hidden layer.

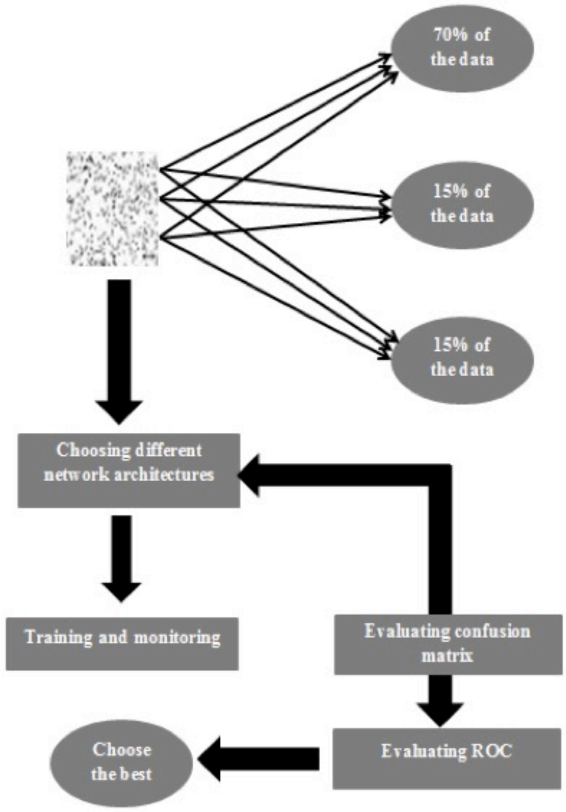

Figure 7- ANN Algorithm

Fig. 7 illustrates the adopted ANN algorithm.

III. Results

Fig. 8 illustrates different trunk inclinations during the task. As seen, 5 different steps can be recognized easily.

TABLE IV- DIFFERENT ANN ARCHITECTURE AD THEIR RESULTING ACCURACY

ANN architecture (hidden layers)	Accuracy result (%)
5	64.1
10	76.0
15	88.5
20	89.9
25	90.6
30	92.8
35	92.6

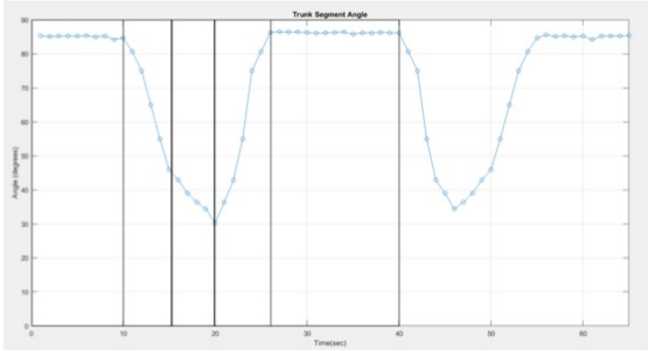

Figure 8- Trunk Angles Graph

Phase 1: window between 0 x 0.2 sec and 10 x 0.2 sec. It displays a constant curve of 87 degrees, which allows us to conclude that the subject is at rest. In fact, these values are related to a perpendicular posture of the trunk respectively to the horizontal (ground) with values approximately close to 90 degrees.

Phase 2: window between 10 x 0.2 sec and 15 x 0.2 sec. It displays a rapid decrease of the trunk inclination curve of 40 degrees, going from 87 degrees to 47 degrees. In includes a forward movement of the trunk since the angle formed with the horizontal is decreasing and the trunk is getting closer to the thigh.

Phase 3: window between 15 x 0.2 sec and 20 x 0.2 sec. The curve is still in a descending direction, but relatively slower than the previous one. Inclination value passes from 47 degrees to 30 degrees where it attempts its minimum value. The trunk still performs a flexion motion.

Phase 4: window between 20 x 0.2 sec and 25 x 0.2sec. A sudden increase of the curve occurs from 30 degrees to 97 degrees concluding that the trunk is moving in the opposite direction of phases 2 and 3: it is getting further from the thigh, and angle between the trunk and ground is getting bigger. The trunk can be said to perform an extension motion.

Phase 5: window between 25 x 0.2 sec and 40 x 0.2 sec. the curve maintains a constant value of 97 degrees, which means that the trunk is in a vertical posture relatively to the ground.

The study has been elaborated for the different features. The features were fed into an artificial neuronal network.

Different ANN architecture accuracy results are presented in table IV. The best results have been obtained for the 30 hidden layers ANN architecture.

Referred to the resulted test confusion matrix, trained inputs provides a total precision of 92.3% and total error of 7.7%, showed in the blue cell of the matrix. Precision and accuracy values corresponding to each output-target class, represented in green cells in the matrix, were as follow:

-Class-target 1: 95.0% and 93.3%.
-Class-target 2: 90.4% and 94.7%.
-Class-target 3: 95.8% and 88.7%.
-Class-target 4: 89.4 and 92.3%.
Results are illustrated in Fig.9.

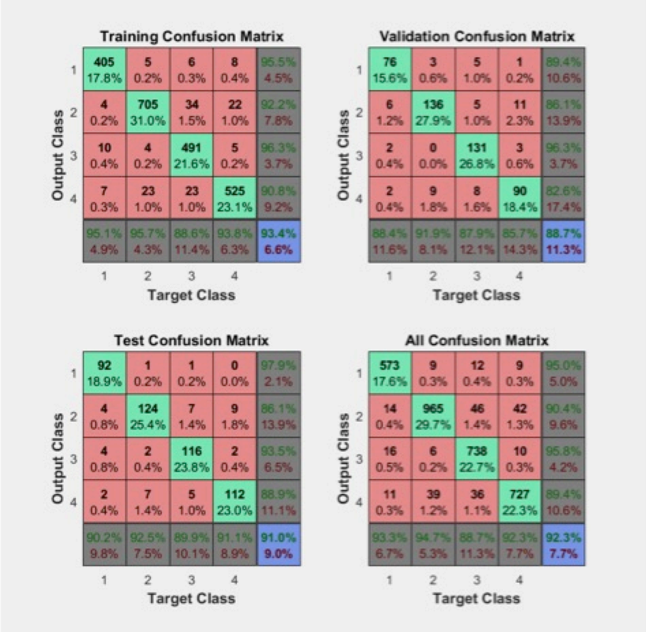

Figure 9- Confusion matrix using 30 hidden layers

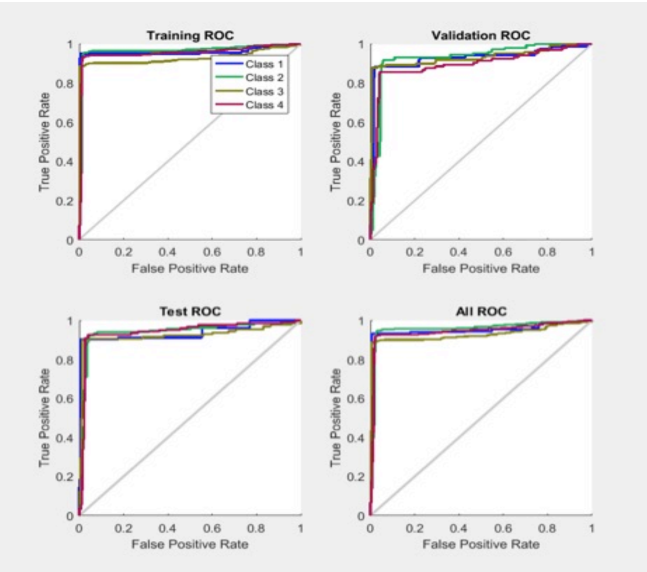

Figure 10- ROC of STS classes using 30 hidden layers

As already stated the best ROC wished, is when the curves starts so close to the y-axis, to reach the closer it can get, to the left-upper corner and then to go parallel with x-axis to reach the closest to the right-upper angle.

However, the 4 curves fits perfectly the description stated above. With area under curves of the 4 classes ranging from, 0.887 to 0.993, this is by far the best classification the MLP can reach. Having a maximum ration of true positive rate over the false positive rate reaching a 0.993 AUC.

IV. Conclusion

We presented a full study of the STS motion based on experiences made on 10 healthy subjects. After understanding different factors that affect the movement and biomechanics behind, we used 6 IMU sensors placed on the metatarsal, shank and thigh segments of the lower limb parts, and 1 IMU sensor on the trunk to extract and record STS motion parameters such as the acceleration, angular velocity, inclination and joint angles. In order to classify this data, we used the Artificial Neural Network Toolbox in MATLAB. By trying different architectures, we were able to each an accuracy of 92.3% using the 30 layers architecture. Finally, we proposed a conceptual algorithm model of the STS motion based on analyzed results and visual observation of different steps during the task. STS analysis has been always an interesting study in different biomedical, biomechanics and physical therapy. Improving our suggested method can be used to study STS performance in elderly and obese people or patients representing a Parkinson disease, impaired postural control, etc. Higher accuracy, using ANN based classification can be reached by increasing number of trials per subject. Furthermore, our extracted features can be used as a reference input to design a Patient Motion Aid exoskeleton to assist disabled people in achieving a STS task by their own.

V. References

[1] Courtney, J. B. (2001). Application of Digital Image Processing to Marker-free Analysis of Human Gait.

[2] Whittle, M. W. (May 12, 2014). Gait analysis: An introduction.

[3] P., B. (2003). Wearable sensors/systems and their impact on biomedical engineering.

[4] Fathima S.M.H.S.S., B. R. (March 21, 2012). Human Gait Recognition Based on Motion Analysis Including Ankle to Foot Angle Measurement.

[5] Raymond Kai-Yu Tong, M. G. (n.d.). practical gait analysis system using gyroscopes in Medical Engineering & Physics.

[6] R. Takeda, S. T. (2009). Gait posture estimation using wearable acceleration and gyro sensors. Journal of biomechanics.