A Neuro-Fuzzy-Based Sensing Approach for the Classification of Emulated Postural Instability

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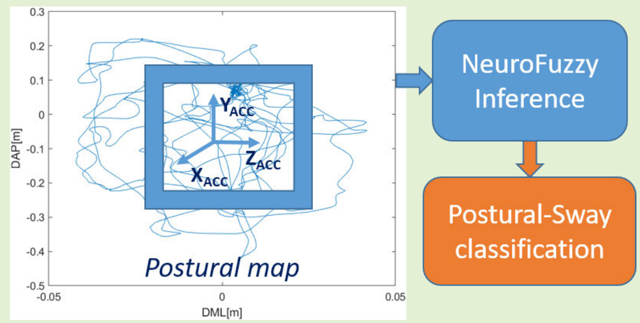
***Abstract*—Assistive technology (AT) helps to assess the daily living of frail people and may have a strategic role to detect and prevent falls. In this article, the task of classifying different classes of postural sway behaviors has been addressed by developing a neuro-fuzzy (NF) inference approach that is robust against noise. The proposed approach classifies four different postural behaviors, namely, stable standing (ST), anteroposterior (AP), mediolateral, and unstable (UNST). The strategy exploits data generated by a wearable sensor node, to be positioned on the user chest. A dedicated experimental setup has been realized to emulate the postural dynamics and generate the dataset. Two novel indices to assess the robustness of the system have been proposed. The first index is a measure of residuals between the predicted and the expected postural status, which equally weights estimations with respect to expected classes. The second metric is a reliability index, which allows for assessing the degree of trust of each estimation performed by the NF inference. Results obtained demonstrate the suitability of the proposed methodology, showing a capability of almost 100% to correctly classify patterns among different allowed classes, with reliability indexes of 97.56% and 98.50% for the training and test patterns, respectively. Also, the robustness of the NF classification algorithm against noisy data has been demonstrated.**



***Index Terms*—Inertial unit, neuro-fuzzy (NF) inference, postural sway behavior classification, system assessment.**

I. Introduction

ASSISTIVE technology (AT) has been applied to address different healthcare needs in the aging population [1]. Several solutions have been developed for monitoring frail subjects' mobility as well as for detecting and preventing falls in different settings [2], [3]. In particular, AT has been proposed for assessing and monitoring elderly subjects suffering from neurodegenerative disorders, including Parkinson's disease (PD), in which different factors may contribute to subjects' health and well-being perception [4]. Postural instability represents a cardinal clinical feature of patients affected by PD. The applications of AT for continuous monitoring of postural instability in frail subjects, particularly in patients affected by neurodegenerative disorders associated with Parkinsonism, focus on: 1) providing objective evaluations on motor disability, response to treatment, and differential diagnosis, which is principally based on diagnostic standardized techniques [5], [6] and 2) the detection and prevention of serious events including falls.

Traditional approaches for the assessment of postural instability are based on the analysis of the time variation of the body's center of pressure (CoP) [7]. For such an analysis, neurologists often adopt clinical tools such as force platforms and vision systems [8], [9]. Unfortunately, such analyses can be performed no more than a couple of times per year and usually in structured environments (e.g., hospitals), thus requiring skilled supervision.

Conversely, the need for monitoring elderly people on their own premises is important as aging seniors prefer to age in place, in the comfort of their homes. This requires the development of low-cost and reliable solutions for the monitoring of postural behaviors in nonstructured environment. Moreover,

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in order to perform a continuous monitoring of the postural sway, a different approach is required, which may conveniently use wearable devices, [10]. Such a monitoring approach will lend itself to an effective strategy for fall prediction.

Although literature may contain a wide variety of approaches to address postural monitoring, no two approaches can be compared due to different modes of data acquisition and lack of any benchmark data. However, when restricted to instability detection or postural sway classification, monitoring strategies may be broadly divided into two approaches, namely, threshold-based algorithms and machine learning methods. Section I-A will discuss the state-of-the-art available in the literature to highlight the contribution of the proposed work.

A. Advancement With Respect to the State-of-the-Art

In [11], a low-cost architecture, based on a Kalman filter approach, is used to analyze the 3-D angular position in eight different locations on the body of the user. Investigation of postural status in patients with Alzheimer disease under different postural stress conditions, with the aim to predict falls, has been carried out in [12], by using data acquired from wearable sensing nodes. In [13], a threshold algorithm to distinguish stable and unstable (UNST) postural using features based on the time evolution of the user's body sway is presented.

A well-elaborated review of the main approaches exploiting inertial measurement units for fall risk assessment is presented in [14]. Neville et al. [15] proposed an inertial sensor node positioned on the posterior trunk, with a specific focus on the system validation against standard approaches, such as using force plate. In order to classify PD patients into motor subtypes, in [16], a system based on a triaxial accelerometer is proposed. A head-mounted wearable IMU, with the aim to provide different measures of postural sway, is investigated in [17]. Lyu et al. [18] performed the validation of an IMU-based solution housed in a pendant worn around the neck. Sensing features embedded in tablet or smartphone have also been explored in the literature [19], as effective tools for posture monitoring.

Several studies have been conducted to assess the best metrics for qualifying and quantifying postural behaviors using the data produced by (inertial) sensing units. In this framework, both time- and frequency-based features have been investigated [20], [21]. As outlined in [21] and [22], time-based features directly estimated by triaxial inertial sensors have been widely used in the literature. Although the time-domain approach has provided good performance, to better characterize the postural dynamics, the frequency content of inertial dynamics has also been investigated [23], [24]. In [25], a comparison among different approaches to detect potential postural instability with a wearable inertial system is provided. In this study, threshold-based algorithms and neuro-fuzzy (NF) models, both processing time-based features or discrete-wavelet-transform-based features, have been compared.

The main limitations of the threshold-based approaches are related to finding a stable separation among different classes of postural behaviors, especially in the presence of noise. Noise affects the assessment reliability; therefore, alternative robust strategies are required. To alleviate this problem, machine learning approaches have been investigated in the literature. Different ML solutions have been adopted for fall detection [26], [27] and posture monitoring [28], [29]. In [28], performances of decision tree classifiers against random forest are investigated to monitor pressure during sitting posture. Sun et al. [29] presented an ML approach to measure the accuracy and feature importance of various postural sway metrics to differentiate individuals with multiple sclerosis from healthy users, as a function of physiological fall risk. A smartphone-based solution, exploiting ML techniques to classify the severity of the motor part of PD patients from their gait, is addressed in [30].

Among other techniques, the use of fuzzy paradigms in the field of posture analysis is well documented in the literature. Associations between gait performance, postural stability, and depression in patients with PD are investigated in [31], by using an adaptive NF system. A fuzzy logic algorithm aimed to investigate users' postures by processing CoP, posture adoption time, and other related features is proposed in [32]. The approach proposed allows for assessing the user posture for well-defined time periods, thus enabling the possibility to perform prompt correction of the user posture.

In [33], a comparative analysis between NF and threshold-based algorithms has been performed, with the aim of classifying the stable and UNST behaviors. While performing postural sway analysis, the possibility to classify among different postural sway behaviors (e.g., standing, anteroposterior (AP) and mediolateral movements, as well as UNST) could represent an added value than merely providing binary discrimination among stable and UNST behaviors. A threshold-based algorithm to accomplish this kind of classification task (four-way classification) has been addressed in [34]. The solution proposed shows a suitable tradeoff between performance and computational requirement. As discussed earlier, such solutions generally lack robustness to noise and perform poorly when presented with noisy data.

In this article, an NF approach aimed to classify among four different postural sway behaviors (stable standing (ST), AP, mediolateral (ML), and UNST) is proposed. This activity represents a meaningful extension to the NF binary classifier provided in [33]. The NF classifier shows better performance in the presence of noise when compared to the threshold-based algorithm provided in [34]. Such an improvement in robustness is achieved at the expense of implementation complexity.

The proposed methodology exploits data generated by a wearable sensor node, to be positioned on the user chest. The aim of this work is to assess the performances of the classification methodology through a set of dedicated metrics, such as the accuracy in properly assigning an unknown pattern to the expected classification task, the reliability of such classification, and the robustness of the approach proposed against noisy data.

The main novelties introduced by this work are summarized as follows.

1) The approach proposed allows for classifying among four different behaviors (ST, AP, ML, and UNST), with

respect to the binary discrimination between stable or UNST behaviors addressed in [33].

2) The use of an NF classification algorithm performs better than the threshold-based algorithm presented in [34], especially in the presence of noisy data.
3) Stabilogram-based features have been used, which implicitly embed subject specification information, such as height or weight or node positioning of the sensors.
4) New metrics are proposed for the assessment of the classification strategy and for the estimation of the reliability associated with each prediction.
5) The robustness of the proposed NF inference has been demonstrated, especially if compared to threshold-based strategies, as supported by results shown in Section V.
6) The use of a wider dataset, including noisy data, with respect to [33], allowing to perform a better assessment of the proposed methodology.

From an application point of view, it is important to note that, although the implementation of the proposed paradigm in embedded systems is out of the scope of this work, the methodology developed is compliant with low-cost solutions running machine learning-based paradigms. The approach proposed will enable the realization of low-cost solutions for the continuous monitoring of the users' postural sway behavior, as the user goes about performing their own everyday activities, thus enabling a home-based (non-structured) monitoring mode. Data provided by the system could be used not only for the prompt monitoring of the user postural sway, thus also enabling fall prediction, but also to assess the degree of severity of potential UNST behaviors (occurrence-frequency analysis) and to define their main characteristics (analysis of recurring postural sway classes).

II. Sensing System and the Dataset

The sensing node used in this work consists of a triaxial accelerometer and a microcontroller-based architecture. The node is based on an STM32 platform, exploiting an ultralow-power ARM Cortex-M4 microcontroller with DSP, and the LIS2DW12 MEMS accelerometer, both by STMicroelectronics. The latter is a 16-bit ultralow-power three-axis linear accelerometer, with output data rates from 1.6 to 1600 Hz and selectable full scales of $\pm 2/\pm 4/\pm 8/\pm 16$ g. A sampling rate of 100 Hz is adopted to acquire data, which are then stored to a memory card. The sensing node performs a continuous acquisition on a 10-s window segment with a 1-s advancement for the next 10-s window segment. The observed time window is well substantiated by findings in the literature [35], affirming that this represents a good compromise between the need for continuous postural sway monitoring and the required computational power.

In order to perform the experimental survey, the dedicated architecture shown in Fig. 1(b) has been adopted. The structure, equipped with the sensor node, allows for mimicking ST, AP, ML, and UNST behaviors. As it can be observed from Fig. 1(a), the sensor node is positioned at a distance from the floor corresponding to standard chest heights. For the sake of clarity, it must be declared that the structure is manually handled to mimic above mentioned postural behaviors of interest.

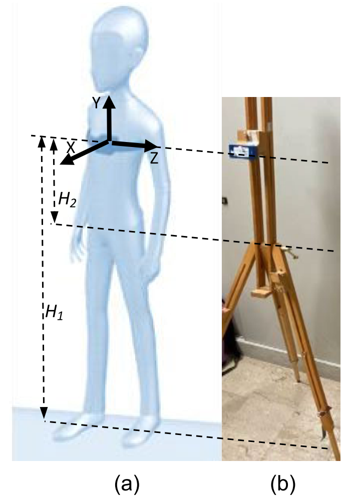


Fig. 1. Architecture, including the sensor node, adopted to simulate different postural sways. (a) Corresponding node position on the human body. (b) Structure, equipped with the sensor node and joints, adopted to reproduce the desired dynamics.

In particular, tilting movements around the belt-positioned joint have been accomplished to emulate mediolateral displacement, while oscillations around the bottom joint have been used to accomplish AP movements. Stable dynamics have been simulated by small displacements around all directions. During the development phase of the postural classification methodology, it has been considered advantageous to use such a structure than using data acquired from real subjects. This helped in building a dataset and quick development of algorithms for appropriately identifying and assessing the NF classification model. Future developments will be dedicated to perform a wide experimental survey by involving end users. However, the suitable robustness of the system to noisy data, discussed in Section V, allows for confirming the validity of the approach proposed through this work, against possible artifacts introduced by the use of a rigid structure compared to human body dynamics.

By exploiting the abovementioned experimental setup, a dataset has been created by mimicking ST, AP, ML, and UNST behaviors. Five different cases have been considered by varying the height of the sensor node. Each case is hence defined by the following two quantities.

H_1: The distance between the node and the bottom joint (on the floor).

H_2: The distance between the node and the belt joint.

The representation of the dataset is given in Fig. 2(a), showing the number of patterns and their distributions among different kinds of postural sway. The dataset has been randomized and, as evidenced in Fig. 2(b), then divided into a training set and a test set. The nonuniform distribution of training and test patterns among classes is motivated by the different complexity associated with classification tasks for each postural dynamic, which increases from ST to UNST behaviors. Since the dataset is quite populated with many examples for each class, it has been decided to stress the prediction capability of the NF model, during the test phase, for those classes presenting dynamics with a higher degree of complexity.

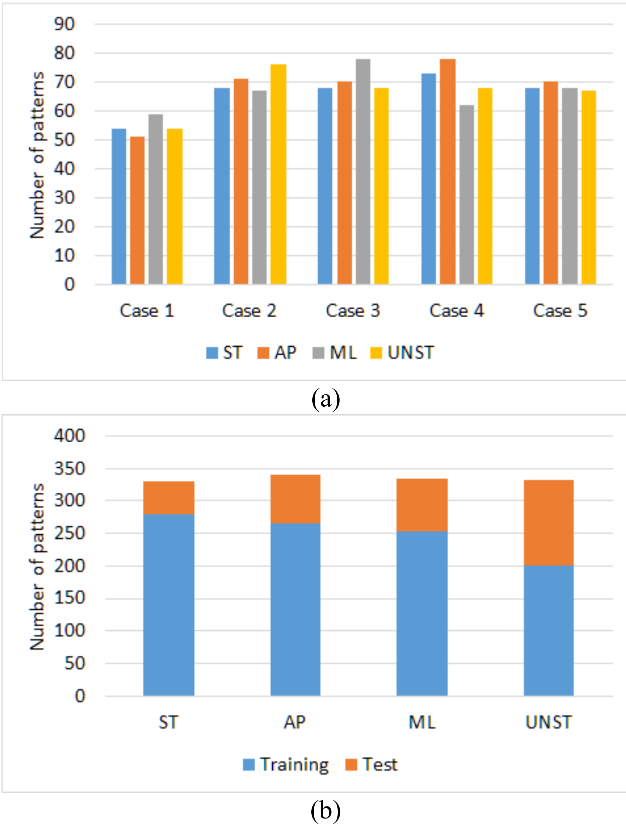


Fig. 2. Representation of the adopted dataset. (a) Number of patterns for each postural sway class and for each considered case. (b) Number of patterns in the training and test datasets per each class.

Moreover, in order to contrast the risk for data leakage between training and test sets, the adopted algorithm has been constrained, thus assuring an equal distribution of patterns coming from different cases between the two abovementioned datasets.

Each pattern is tagged by a code (class, C_i, $i = [0, 2, 4, 6]$: 0 for ST behavior, 2 for AP movements, 4 for ML movements, and 6 for UNST behaviors. The realized dataset has been used to set and test the proposed NF classification algorithm.

III. Postural Sway Classification Strategy

The methodology investigated through this work aims to classify among the following four different postural dynamics: ST, AP, ML, and UNST. The first step accomplished toward the achievement of this task was dedicated to estimate the time evolution of the AP and mediolateral displacement (D_{AP} and D_{ML}) [25], [33], from the three acceleration components provided by the sensor node. Starting from such dynamics (whose combination is called stabilogram), it is possible to define a set of features that are strategic for the implementation of the classification task.

A. Adopted Set of Features

To assess the user postural behavior, different characteristics can be extracted from the stabilograms. The main features considered in this work are summarized in Table I [21]. Such quantities have been selected among others available in the literature, based on: 1) the criterion of easy implementation on embedded systems [25] and 2) the study presented in [34]

TABLE I
Features Extracted by Stabilogram

Feature	Description
D_{AP}^{max} (m), D_{AP}^{min} (m)	Maximum and minimum displacement in the AP direction.
D_{ML}^{max} (m), D_{ML}^{min} (m)	Maximum and minimum displacement in the ML direction.
$CEA_{95\%} = \pi * a * b$ (m^2) $a = CSF * \sigma_{AP}$ (m) $b = CSF * \sigma_{ML}$ (m)	Confidence Ellipse Area which includes 95% of the stabilogram plot. The two terms a and b represent the two semi-axes of the ellipse. CSF is a Confidence Scaling Factor whose value, in the case of the 95% ellipse, is 2.4477. σ_{AP} and σ_{ML} are the standard deviations of the D_{AP} and D_{ML}, respectively.
$RMS_d = \sqrt{\frac{\Sigma_{1=1}^{N}\left(d_P(i)\right)^2}{N}}$ (m)	Root Mean Square displacement. *dp(i)* is the distance between two adjacent points on the stabilogram.

to assess the reliability associated with the use of different features, which demonstrated that maximum AP and mediolateral displacements, the confidence ellipse area, and the root-mean-square displacement are the most convenient features.

It must be considered that the estimation of features requires the implementation of basic equations shown in Table I, whose computational timings are negligible with respect to the adopted classification rate, which represents the dominant time scale.

As discussed in [13], since the postural sway should be assessed during the static posture of the user, it is important to highlight that the effects of dynamics introduced by daily activities, such as walking, must be identified and removed.

B. NF Postural Sway Classification Approach

The procedure adopted for both the identification of the NF algorithm and its assessment is shown in Fig. 3(a). A Sugeno-type Fuzzy inference system is used, which is computationally efficient and shows good performances in performing classification tasks [36]. As shown in Fig. 3(b), the NF model uses the four features shown in Table I as inputs and provides at the output the predicted class of postural sway, C_i^{Pred}.

The model has been implemented by using dedicated libraries available in MATLAB. In particular, the "genfis" function allows for generating an initial structure by extracting a set of rules that model the data behavior. A subtractive clustering is exploited to fix the number of rules and antecedent membership functions, while a linear least-squares estimation is used to determine each rule's consequent equations. The training step has been implemented through the "anfis" function. The latter generates a single-output Sugeno fuzzy inference system and tunes the system parameters on input–output training data through a combination of the least-squares and backpropagation gradient descent methods. A grid partitioning approach is used to finalize the model. The paradigm, by exploiting the "evalfis" function, provides the

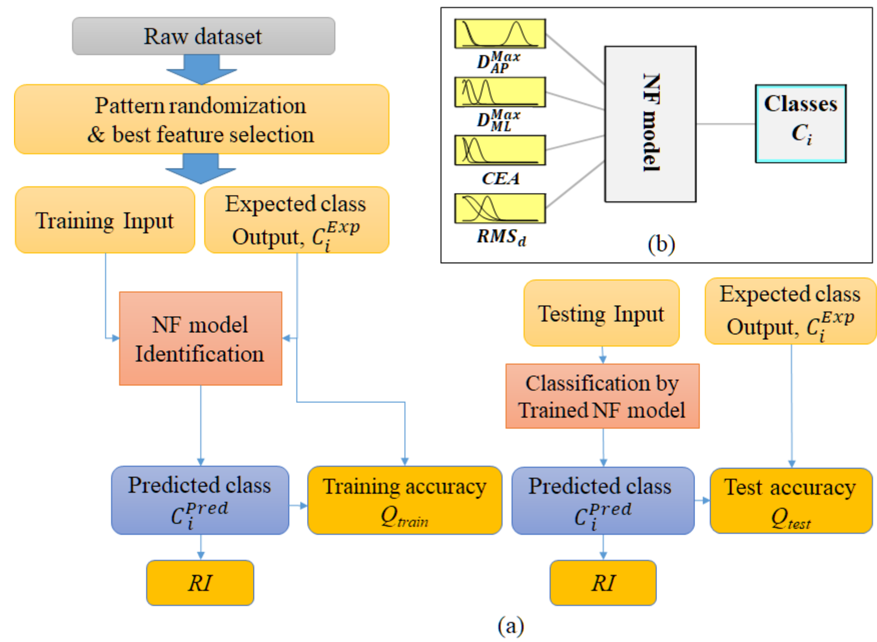


Fig. 3. Approach adopted to identify and assess the NF postural sway classification paradigm. (a) Flow diagram of the approach developed. (b) Adopted NF model.

TABLE II
DETAILS OF THE FUZZY MODEL ADOPTED FOR THE POSTURAL SWAY BEHAVIORS ASSESSMENT

Property	Value/Description
Inputs/Outputs	[4 1]
Number and type of InputMFs	[4 4 4 4], Gaussian
Number and type of OutputMFs	4, Linear
NumRules	4
DeFuzzification Method	Weighted-Average

predicted postural status, C_i^{Pred}. Moreover, the latter is rounded to the closest class, thus defining the rounded prediction of the postural status, C_i^{Round}. Further specifications of the NF model are given in Table II.

Once the model has been estimated, the test dataset has been used to assess the performance of the proposed methodology during the development phase. To such aim, the following index has been used, which exploits residuals between the predicted and the expected postural status, equally weighting estimations' divergence with respect to the expected class:

$$Q = 100\left[1 - \frac{\sum_{i=1}^{N} \gamma_i}{N}\right]$$
$$\gamma_i = \begin{cases} 0, & \text{if } \left|C_i^{\text{Round}} - C_i^{\text{Exp}}\right| = 0 \\ 1, & \text{if } \left|C_i^{\text{Round}} - C_i^{\text{Exp}}\right| > 0 \end{cases} \tag{1}$$

where N is the number of the considered patterns.

Since the index in (1) is computable only during the training phase, where the expected class, C_i^{Exp}, is known, in real cases, where unknown patterns are processed, a different index is required. To such aim, the following quantity has been defined, which allows for assessing the reliability of each estimation performed by the NF inference:

$$\text{RI} = 100\left[1 - \min\left|C_i^{\text{Pred}} - C_i\right|\right]. \tag{2}$$

The index RI computes the minimum distance among the NF estimation, C^{Pred}, and all the possible classes, C_i. Since classes, C_i, are separated by a distance equal to 2, the RI collapses to very small values in case the NF estimation is very close to the separation element among two consecutive classes.

In order to estimate the overall performances of the developed methodology, the following indexes have also been computed for the whole datasets:

$$\text{RI}_{\text{Mean}} = \text{mean}(\text{RI}) \tag{3}$$
$$\text{RI}_{\text{Std}} = \text{std}(\text{RI}) \tag{4}$$

where mean(.) and std(.) are the average and standard deviation operators, respectively.

The above indexes will be used in Section IV to assess the performances of the NF classification tool. While interpreting results, it must be highlighted that RI values are bounded to 100%.

IV. RESULTS

In order to estimate the optimal behavior of the NF model, different values of the "range of influence of the cluster center" have been investigated. This quantity defines the range of the search for clusters in a dataset.

The behavior of indices given in (1), (3), and (4) for influence range values belonging to (0.1–0.6) is shown in Fig. 4 for the training and test datasets. As it can be observed, the optimal value of the range of influence optimizing the Q and RI indices is 0.18.

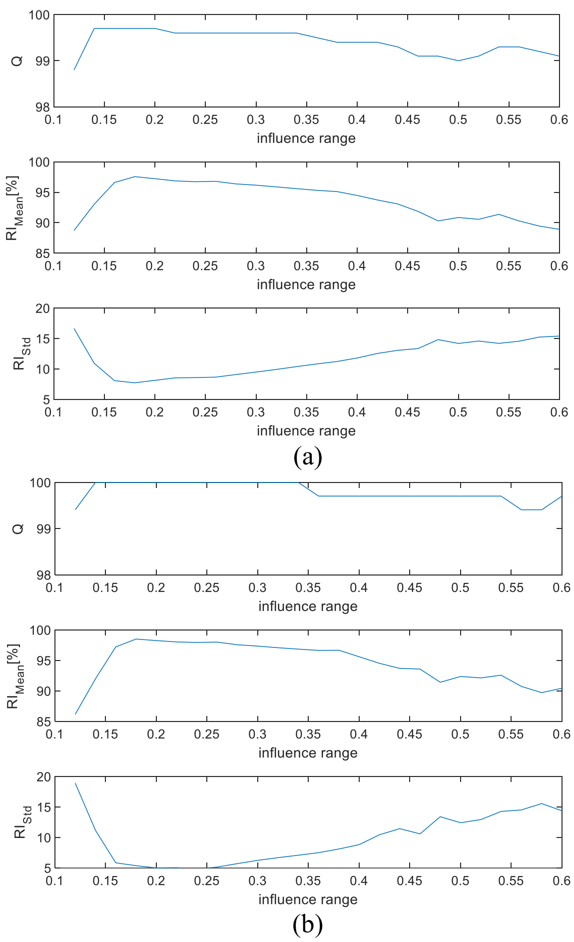


Fig. 4. Behavior of the performance indexes versus the "influence range," for (a) training and (b) test dataset.

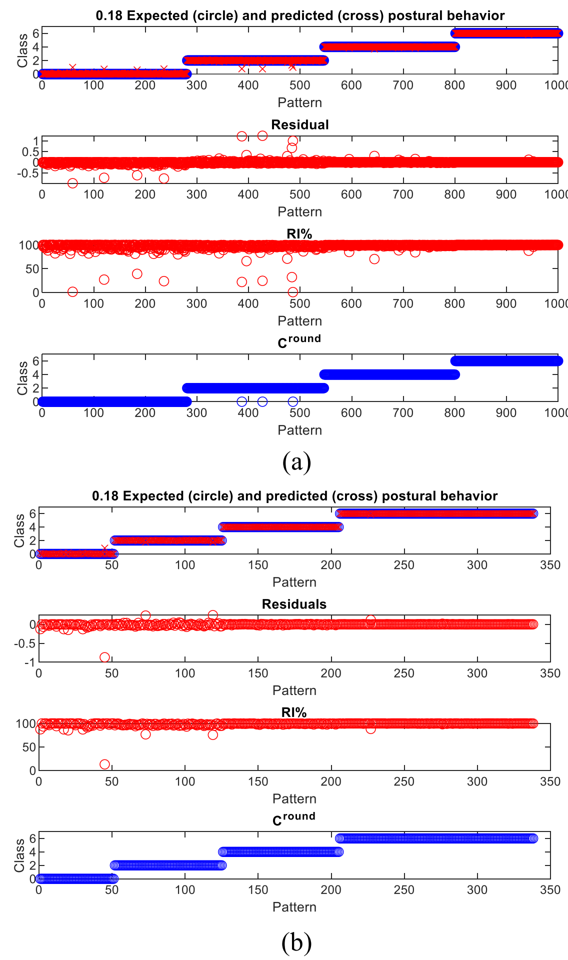


Fig. 5. Behaviors of the proposed methodology in the optimal case (influence range of 0.18). (a) Training dataset. (b) Test dataset. Each frame presents, from the top to the bottom: the comparison between the expected postural behavior (circles) and the one predicted by the NF algorithm (crosses), the residuals, the reliability index RI, and the rounded postural classification, C^{round}.

Performances of the classification algorithm, in case of a range of influence equal to 0.18, are shown in Fig. 5. In particular, the comparison between the expected postural sway (represented by the "circle" symbol) and the one predicted by the NF algorithm (represented by the "cross" symbol) is shown, along with residuals between expected classes, C^{Exp}, and predicted classifications, C^{Pred}, the reliability index, RI, and the rounded classification index, C^{Round}. Obtained results, shown in Fig. 5 both for the training and test datasets, provide a clear representation of NF algorithm performances, in terms of accuracy in predicting the correct class for each pattern and the corresponding reliability of each prediction.

Values of indices given by (1), (3), and (4) are reported in Table III, both for the training and test datasets. As it can be observed, the NF model shows suitable performances, both in terms of the system capability to correctly classify the postural sway behavior, Q, and the associated RI.

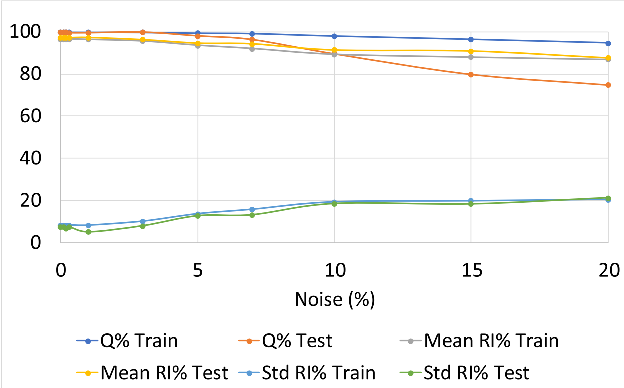
The latter, for the test dataset, shows a mean value of 98.50% with a standard deviation of 5.38%.

Table III also shows the performances obtained by feeding the threshold-based algorithm discussed in [34] with the same dataset adopted through this work. The obtained results allow to affirm better performances of the NF inference system proposed with respect to traditional threshold-based algorithms. It is worth noticing that the obtained results are comparable to ones provided by the NF algorithm presented in [33], addressing the task of binary discrimination between stable and UNST dynamics.

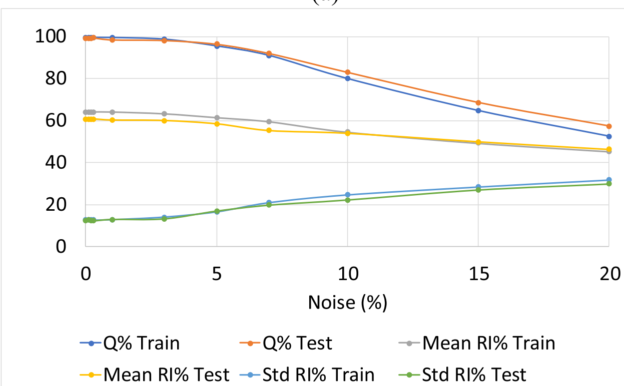
TABLE III
PERFORMANCES OF THE CLASSIFICATION ALGORITHMS

Data/index	Q%	RI_{MEAN}%	RI_{Std}%
Threshold based algorithm [34]			
Training Dataset	99.60	64.15	12.60
Test Dataset	99.10	60.58	12.50
NF algorithm (this work)			
Training Dataset	99.80	97.56	7.72
Test Dataset	100.00	98.50	5.38

The postural sway classification strategy has also been investigated against a noisy dataset. To such aim, the original dataset has been corrupted by different levels of Gaussian noise. In order to ensure that the noise produces a homogenous effect for all considered features, each feature has been added with a noise level whose standard deviation is expressed as the percentage of the maximum value assumed by that feature through the whole dataset. The following levels of noise have been used: 0.1%, 0.2%, 0.3%, 1.0%, 5.0%, 7.0%,



(a)



(b)

Fig. 6. Investigation on the robustness of the postural sway classification methodology against noisy data. (a) NF model. (b) Threshold-based algorithm.

10.0%, 15.0%, and 20.0%. Results of this analysis are given in Fig. 6(a), showing the effect of the noise on Q and RI indices. As it can be observed, the NF algorithm is quite robust against the noisy dataset, especially in terms of reliability associated with estimated classes.

For the sake of completeness, the same analysis has been performed by using the same dataset with the threshold-based algorithm presented in [34]. Results, shown in Fig. 6(b), clearly highlight that the NF approach performs better than the threshold-based algorithm, of course at the expense of an increased implementation complexity.

In terms of computational timing, once the inference model has been trained, the prediction is very fast and negligible with respect to the adopted postural sway classification rate of 1 Hz. Of course, such performances also depend on the characteristics of the computing device. A dedicated test has been accomplished by using an 11th Gen Intel[1] Core[2] i7-1195G7@2.90 GHz and 16.0-GB RAM. This test revealed computational timings, for predicting the whole test dataset, equal to 0.0037 and 8.5888 ms for threshold and NF algorithms, respectively. Although the NF inference is more time-demanding, the obtained results demonstrate that this approach is fully compliant with real applications requiring the classification among different kinds of postural dynamics, especially considering the adopted classification rate of 1 Hz.

[1]Registered trademark.
[2]Trademarked.

V. Conclusion and Future Work

In this work, a neuro-fuzzy approach is proposed to perform a reliable classification among different postural sway behaviors.

The main reasons driving the choice of using an NF approach rely on the consideration that it is not easy to identify reliable separation elements, especially in the presence of noise, to implement threshold-based classification of different postural behaviors. This has been already demonstrated in the literature and explicitly discussed in [33]. In particular, the NF approach has been chosen against other machine learning-based strategies due to the auto-setting characteristics of NF algorithms. Results obtained in this article demonstrate a good performance of the NF inference system for the postural sway classification task. Indices have been defined to assess the behavior of the proposed approach.

A near-perfect classification has been demonstrated both for the training and test datasets, with a reliability index of 97.56% and 98.50%, respectively.

The robustness against noisy data has also been investigated, which revealed a remarkable performance of the NF algorithm both in terms of the proposed Q and RI indices.

Moreover, results obtained by using the NF inference have been compared to performances of the threshold-based algorithm investigated in [34], clearly demonstrating the advantages of the NF approach.

The results obtained using the proposed approach confirm the reliability of the system to perform well in the presence of noise. This encourages one to extend the approach to fall prediction, along with reliable monitoring of users' postural behaviors.

The main limitation of the proposed study is related to the choice of emulating postural dynamics by using the dedicated set-up, which has been considered a convenient approach during the development phase of the postural classification methodology. The main reasons are related to the difficulty and risks associated with the involvement of real users, which can be avoided during the development phase, with the advantage of rapidly generating a wide dataset. Of course, validation and refinement of the proposed approach by tests with real users are the mandatory steps, which will be accomplished as a further development of this work. It must be highlighted that the results shown in Section IV, investigating the methodology robustness against noisy dataset, support the reliability of assessment performed by emulated patterns.

Future efforts will also be dedicated to the implementation of the proposed approach by embedded architectures, compliant with the need for wearable and low-cost monitoring system. Actually, such systems would enable real-time estimation of the postural sway and provide alerts in the case of UNST behaviors. Such a strategy would allow also for assessing the degree of severity of potentially UNST behaviors, performing analytics on occurrence frequency and characteristics of detected postural sways.

Although NF inference shows the add value of self-generating an initial structure by extracting a set of rules that models the data behavior, the investigation of other machine learning methods, such as multilayer perceptron, deep learning, or meta learning, will be considered as possible benchmarks.

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