Enabling Smartphone-centric Platforms for In-Home Rehabilitation: a Comparison among Movement Recognition Approaches

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***Abstract*—In-home physical therapy is one of the best options for many individuals and families thanks to its convenience and because it makes possible to receive professional care in the comfort of your own home. To enable this therapeutic approach, this paper proposes the employment of a smartphone-centric platform for in-home rehabilitation. The platform helps physicians to monitor the patients remotely so avoiding hospitalization therapies that can be stressful. In more detail, the work is focused on the Movement Recognition (MR) functionality of the aforementioned platform. It compares algorithms, which process the signal provided by the embedded accelerometer sensor of the smartphone, able to recognize if a patient had performed the movements requested by the physicians. The provided performance comparison of different MR techniques shows that Support Vector Machine-based approaches have very good accuracy (up to 99.3%), thus making the in-home physical therapy reliable.**

I. Introduction

Physical Medicine and Rehabilitation (PM&R), also called physiatry, is the branch of medicine emphasizing the prevention, diagnosis, and treatment of nerves, muscles, bones and brain disorders that may produce temporary or permanent impairment. In-home physical therapy is one of the best options for many individuals and families. One of the most obvious benefits of in-home therapy is convenience: it can be difficult for patients with physical conditions to travel to and from a therapists office to receive care. In-home therapy makes possible to receive professional care in the comfort of your own home, allowing you to use all your energy for healing and not making travel arrangements. Moreover, outpatient physical therapy can be stressful, and offices are often noisy and crowded. In-home therapy enables to focus on each patient for longer and many patients feel that the quality of care they receive is superior. A really important factor, moreover, concerns the faster health progress: considerable evidence has been gathered showing that the personalized care you receive from in-home therapy actually boosts the progress of healing. Performing exercises in a stress-free environment can be more focused and intensive.

The major drawback of physical therapy at home is that it is generally more expensive than outpatient care.

A person-centred modern tele-monitoring platform for PM&R may be structured into four essential elements: 1) people who need rehabilitation; 2) sensors/devices/systems actually measuring physical quantities; 3) hubs, which collect the measurements and send them to the final destinations through telecommunication networks; 4) final destinations, physicians and other health care providers or family care givers. Smartphones can play an important role by exploiting the “hub+sensor+processor” paradigm [1].

Upper extremity complications are common following stroke and may be seriously debilitating. Regaining mobility in upper limbs may be difficult and long-lasting. Activity-based rehabilitation is fundamental to improve upper-limb motor function. Lack of arm mobility directly affects all the normal activities of daily life and seriously limit a person independence. For these reasons, upper limbs rehabilitation is extremely important.

This paper is focused on a rehabilitation platform, that exploits smartphone’s capability, able to provide in-home therapy to patients who need to regain upper limbs mobility. The implementation over smartphone of accelerometer signal processing algorithms allows avoiding the employment of ad-hoc specific equipments to monitor a set of simple physical exercises.

II. Related Works

In recent years, the use of smartphones for home-care or e-Health applications has gathered great interest [2]. The smartphone has been proved helpful for cardiac rehabilitation in postmyocardial infarction patients [3] and for monitoring and tracking progresses of heart-failure patients [4]. Evaluating and tracking the daily activity of a patient is crucial for monitoring different type of patients. For example, in pulmonary rehabilitation, it has been proposed the use of a smartphone application that suggests respiration exercises in which patients are supported remotely and given automatic feedback during the exercise [5].

The smartphones, carrying an accelerometer sensor, have been often used to monitor the activity of patients. For a cardiac rehabilitation application, a step counter has been used to evaluate the daily activity of the patients [6].

Many works aim to classify the activity of the patient, by processing the accelerometer signal. Some of these works use *ad hoc* devices attached to the user body [7], but most of them exploit the in-built accelerometer of the smartphones [8]. Recognizing arm movements have become very attractive for

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detecting gestures and interact with consumer electronics and smartphones. With the recent diffusion of smartphones, many works have been proposed to detect gestures by using a hand-held device. The detection of gestures have been performed by exploiting different classifiers, such as Hidden Markov Models [9]–[12] and Support Vector Machines [10]. These methods require an extensive training phase to be effective. To overcome this problem, works based on Dynamic Time Warping (DTW) have been proposed [13].
DTW was originally developed for speech recognition applications [14], [15] but it has also been applied in many other fields such as economics [16], chemistry [17], [18] or biology [19]. It has also been widely applied to motion detection [20]–[23].

III. Platform Description

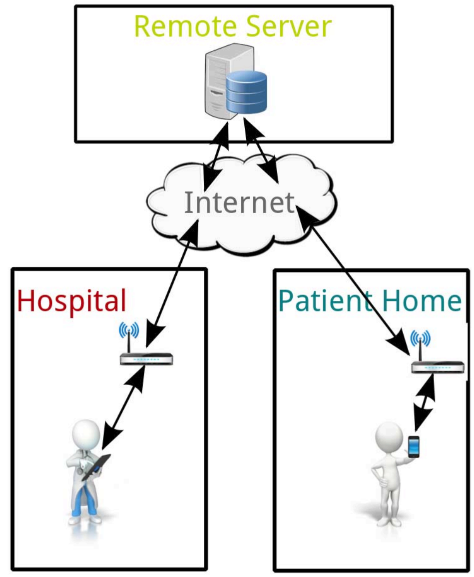
Telemedicine and e-Health defined a cost-effective and secure use of information and communications technologies in the support of health and the related fields [24]. They provide healthcare services through Information and Communications Technologies (ICT) overcoming the geographical separation of patients and providers [4]. Specifically, tele-monitoring is widely used and is beneficial for common problems such as diabetes, heart failure, and rehabilitation. It represents the framework in which this paper is developed exploiting the tools offered by technology: telecommunications networks and smartphones.
Figure 1 shows the proposed eHealth platform considered in this paper, inspired by the one already reported in a previous proposal of the authors [1]. The physician requests the patient to perform a set of daily exercises. The patient phone guides the user through the exercise session by suggesting movements to perform and checks if he actually does them correctly. This information is stored in a remote database that can be always accessed by physicians. Using this system, the physician can monitor the improvements of the patient in real-time and take actions consequently, such as, for example, changing the type of movements to perform or raise the number of exercises per session.

The scenario is focused on the patient who needs to perform some physical rehabilitative exercises (described in Section IV) by using his upper limbs. Such exercises are monitored by the smartphone, exploiting the “hub+sensor+processor” paradigm, already reported in [4]. The employment of smart-objects such as smartphones, helps physicians to monitor the patients and also avoid the outpatient physical therapy. Thanks to a Movement Recognition (MR) algorithm, which processes the signal provided by the embedded accelerometer sensor, the smartphone is able to recognize if the patient has performed all the movements the physician requested. Then, such information is automatically sent to the hospital’s server where the medical staff can control the progresses.

IV. The Movement Recognition Problem

Movement Recognition (MR) algorithm is based on processing and classification of data sensed by the smartphone-embedded accelerometer. MR is aimed at recognizing 6 different classes of movement, taken from [26] and considered of interest in the context of this paper:

Fig. 1: The proposed eHealth platform.



1) *Arm circles (AC)*: the user is standing, his arms are lifted straight out to his sides at shoulder height. The user starts moving his arms in a circular pattern (clockwise or counter-clockwise, indifferently) with palms facing down.
2) *Arm presses (AP)*: the user is standing with his arms along the body, his palms are facing behind him. He pushes his arms as back as he can and then he gets back to the starting position.
3) *Arm twist (AT)*: the user is standing, his arms are lifted straight out to your sides at shoulder height. The user starts extending and twisting his arms. His palms move accordingly.
4) *Curls (C)*: the user is standing, his elbows are lifted out to his sides at shoulder height, his hands are in front of his chest, palms down. The user, without moving his elbows, draws a circle with his hands on the vertical plane, once he reaches the starting position he draws a circle backwards, getting back again to the starting position.
5) *Seaweed (SW)*: the user is standing, his elbows are lifted out to his sides at shoulder height, his hands are in front of his chest, palms down. The user moves his hands crossing them in front of his face and gets back to the starting position.
6) *Shoulder rolls (SR)*: the user is standing with his arms along the body, his palms are facing the user body. The user starts rolling his shoulders (clockwise or counter-

clockwise, indifferently) without flexing his arms or changing the hand orientation.

The smartphone employed during the tests integrates a triaxial, piezoresistive accelerometer that measures the acceleration values on the three Cartesian axes in $[m/s^2]$. MR has been performed by comparing three different classifiers, often employed in pattern recognition or machine learning problems: *i)* Support Vector Machine (SVM), *ii)* C4.5 Decision Tree (DT), *iii)* and Dynamic Time Warping (DTW). The first two classifiers work by separating the features hyperspace while the last one performs an overall temporal analysis. All the classifiers are briefly described in the next sections.
In this paper we denote with $s_{j,n}$ the n-th sample of the j-th axis of the accelerometer signal, $j \in \{x, y, z\}$. In the remaining of the paper, for the sake of readability, when it is not strictly necessary to distinguish between the three axes components, we will use a notation which omits the axis index j. Consequently, the single accelerometer sample containing the three axis components $\{s_{x,n}, s_{y,n}, s_{z,n}\}$ will be simply denoted with s_n.
We define f as the index of a frame containing N three-axis accelerometer samples s_n. In order to be classified, a feature vector must be associated to each individual accelerometer frame. A crucial problem for all systems performing pattern recognition is the selection of the best feature set to characterize their signals. In the literature, many works have proposed different features that allow achieving good performances in terms of accuracy of the activity or movement recognition. For the f-th frame, a feature vector $\mathbf{X}_f$ is computed. Let us denote with V the number of feature vectors that compose a single acquisition. Consequently, we can define $\mathbf{\Omega}$ as the $V \times |\mathbf{X}|$[1] matrix containing all the feature vectors as follow:

$$\mathbf{\Omega} = \begin{bmatrix} \mathbf{X}_1 \\ \vdots \\ \mathbf{X}_n \\ \vdots \\ \mathbf{X}_V \end{bmatrix} \tag{1}$$

We define $\mathbf{L}$ as the vector containing all the movement classes (2).

$$\mathbf{L} = \{AC, AP, AT, C, SW, SR\} \tag{2}$$

A. The Support Vector Machine Classifier

Support Vector Machine (SVM) is a powerful supervised learning technique for pattern classification. It maps inputs into a higher-dimensional space and then separate classes with a hyperplane. In the literature of the field, together with Decision Tree (DT) and Dynamic Time Warping (DTW), SVM is one of the most employed classifier for movement and activity recognition. As reported by [27], two are the most common approaches trough which the SVM algorithm can be employed for multi-class classification: *i) One-Against-All* (OOA) and *ii) One-Against-One (OAO)* . The former constructs one SVM model for each class of the considered application. The single SVM is trained by employing all the features belonging to that class with positive labels and all the other feature vectors belonging the the other classes with negative labels [27] (*e.g.,* one SVM for the *Curls-NotCurls* case). The same approach was already been used in the voice processing applicative scenario (see [28] and [29]).
The single SVM constructed for the L_h class ($h \in [1, |\mathbf{L}|]$), reported in its Wolfe-dual form, can be stated as follow:

$$\underset{L_h, h\in[1,|\mathbf{L}|]}{\mathbf{SVM}} : \min_{\boldsymbol{\lambda}} \mathbf{\Gamma}(\boldsymbol{\lambda}) = \frac{1}{2}\sum_{f_1=1}^{|\mathbf{F}|}\sum_{f_2=1}^{|\mathbf{F}|} \hat{Y}_{f_1}\hat{Y}_{f_2} \cdot \phi\left(\boldsymbol{X}_{f_1}, \boldsymbol{X}_{f_2}\right)\lambda_{f_1}\lambda_{f_2} + -\sum_{f_1=1}^{|\mathbf{F}|}\lambda_{f_1}, \tag{3}$$

$$\sum_{f_1=1}^{|\mathbf{F}|} \lambda_{f_1}\hat{Y}_{f_1} = 0,$$

$$0 \le \lambda_{f_1} \le C, \ \forall f_1.$$

where $\boldsymbol{\lambda} = \{\lambda_1 \ \cdots \lambda_{f_1} \ , \lambda_{f_2} \ \cdots \lambda_{F\{i\}}\}$ represents the *Lagrangian Multipliers* vector for the set L.
The scalars $\hat{Y}_f \in [-1, 1]$ are the numeric binary labels associated to the semantic labels Y_f of the feature vectors $\boldsymbol{X}_f$. Specifically, they are defined as follow:

$$\hat{Y}_f = \begin{cases} 1, & \text{if } Y_f \equiv L_h \\ -1, & \text{otherwise} \end{cases} \tag{4}$$

The *One-Against-One* approach relies on constructing classifiers where each one is trained by using data from two classes. Differently from the *OAA* approach, the *OAO* method aims at training different SVMs by using mathematical combination (*i.e.,* the order of selection does not matter) of all the classes present in the considered set at group of two (*e.g.,* one SVM for the *Curls-SeaWeed* case). Exploiting the binomial coefficient formula, this lead to obtain $\binom{6}{2} = \frac{6\cdot(6-1)}{2} = 15$ different SVMs. In this paper, both of them have been tested and the results they provided are shown in the related section. The mathematical formulation of the SVM-*OAO* is the same of Eq. (3). The sole difference relies in the definition of the numeric binary labels $\hat{Y}_f$. In the case of *OAO*, they are computed as follow:

$$\hat{Y}_f = \begin{cases} 1, & \text{if } Y_f \equiv L_h \\ -1, & \text{if } Y_f \equiv L_k \end{cases} \tag{5}$$

Two are the main SVM parameters. The quantity C ($C > 0$) is the *Complexity* constant. It determines the trade-off between the flatness (i.e., the sensitivity of the prediction to perturbations in the features) and the amount by which misclassified

[1] $|\mathbf{X}|$ denotes the cardinality of the set $\mathbf{X}$.

samples are tolerated. A higher value of C means that more importance is given to minimising misclassification. Both OAO and OAA approaches employ a non-linear SVM that relies on the use of a Gaussian Kernel (denoted with $\phi\left(\right)$ in Eq. (3)). Specifically, γ, used in non-linear SVMs, is a Gaussian Kernel parameter. A γ too large could provide a probable overfitting of the classifier. On the other hand, a smaller γ value could lead to a model not able to capture the complexity of the data.

B. The C4.5 Decision Tree Classifier

Decision Trees (DT) is a non-parametric supervised learning algorithm employed both for classification and regression. It aims at creating a model that recursively partitions the feature space such that the samples with the same labels are grouped together. The deeper the tree, the more complex the decision rules and the higher the risk of over-fitting. On the other hand, a smaller tree provides simpler decision rules and a more generic DT but with lower classification accuracy. The DT employed in this paper is the C4.5, also implemented within *Weka* [30]. The algorithm is ruled by 2 parameters: the *ConfidenceFactor* and the *MinNumberObj* per leaf. The former is a pruning-related parameter while the latter is a parameter related to the minimum number of instances a left must classifies to be considered as so. We define a *split* as an association $\theta\left(r,\epsilon\right)$ where the single feature $X_r \in \mathbf{X}$ is subject to the threshold ϵ which separates the data into $\boldsymbol{\Omega}_{left}\left(\theta\right)$ and $\boldsymbol{\Omega}_{right}\left(\theta\right)$ subsets. Specifically,

$$\theta\left(r,\epsilon\right) \rightarrow \begin{cases} \boldsymbol{\Omega}_{left}\left(\theta\right), & \forall\left(\mathbf{X},Y\right)|X_r \leq \epsilon \\ \boldsymbol{\Omega}_{right}\left(\theta\right), & \forall\left(\mathbf{X},Y\right)|X_r > \epsilon \end{cases} \tag{6}$$

The *split* θ must be carefully chosen by choosing a proper criterion that allows deciding which feature must be used and with which threshold. To do so, we define the *purity* function $G(\boldsymbol{\Omega},\theta)$, a measure of how well the classes are separated.

$$\begin{aligned} G(\boldsymbol{\Omega},\theta) = & \frac{|\boldsymbol{\Omega}_{left}|}{|\boldsymbol{\Omega}_{left}|+|\boldsymbol{\Omega}_{right}|} \cdot H\left(\boldsymbol{\Omega}_{left},\theta\right) + \\ & + \frac{|\boldsymbol{\Omega}_{right}|}{|\boldsymbol{\Omega}_{left}|+|\boldsymbol{\Omega}_{right}|} \cdot H\left(\boldsymbol{\Omega}_{right},\theta\right) \end{aligned} \tag{7}$$

where H is the *entropy* function. Higher values of $G(\boldsymbol{\Omega},\theta)$ represent a bad separation between the classes while lower values mean that the *split* is able to properly separate the classes.
The criterion for deciding the best *split* is the *information gain*, defined as follow:

$$IG(\boldsymbol{\Omega},\theta) = H\left(\boldsymbol{\Omega}\right) - G(\boldsymbol{\Omega},\theta) \tag{8}$$

Finally, the choice of the best *split* falls on the value of θ which provides the best result in terms of minimizing the *information gain*. In formula:

$$\theta^* = \arg\min_{\theta}\left[IG(\boldsymbol{\Omega},\theta)\right] \tag{9}$$

The C4.5 DT algorithm iteratively recurse until the maximum allowable depth is reached and the stop condition is satisfied. In this paper the employed stop condition is that a terminal node (called *Leaf*) contains less samples than a predefine threshold, called *MinNumberObject*.

C. The Dynamic Time Warping Classifier

The Dynamic Time Warping (DTW) [31] is a technique that finds an optimal alignment between two sequences. It allows a non-linear mapping of a signal to another by minimizing the distance between the two. We note with $\mathbf{S^A} = \{s_1^A,...,s_n^A,...,s_N^A\}$ and $\mathbf{S^B} = \{s_1^B,...,s_m^B,...,s_M^B\}$ the two sequences we want to compare, with $n \in [1,N]$ and $m \in [1,M]$. In this paper they are sequences of values of the sampled accelerometer signal. Given two generical sequences of accelerometric data $\mathbf{S^A}$ and $\mathbf{S^B}$, the DTW distance is a positive number that is small if $\mathbf{S^A}$ and $\mathbf{S^B}$ are similar and is large otherwise. The algorithm is ruled by the W parameter which is a local constraint to limit the search for the match between the signals distance.
For the h-th class ($h \in [1,|\mathbf{L}|]$) belonging to the class set $\mathbf{L}$ a Reference Sequence (RS) is chosen. This sequence, denoted with $\mathbf{S}^{\mathbf{R}\{h\}} = \{{s^{R^h}}_1,\ldots,{s^{R^h}}_q,\ldots,{s^{R^h}}_Q\}$, $q \in [1,Q]$, is the RS for the class L_h and it is used for the comparison. Every time an unknown accelerometer signal sequence $\mathbf{S^U} = \{{s^U}_1,\ldots,{s^U}_r,\ldots,{s^U}_R\}$, $r \in [1,R]$ has to be classified, the system compares it with all the RSs by measuring the *DTW* distances between them. It is worth noting that DTW algorithm is robust with respect to the length of sequences: DTW distance does not significantly change if Q and R have not the same value.
The decision h^* is the index of the class whose RS is DTW-closer to the $\mathbf{S^U}$ sequence, see Eq. (10).

$$h^* = \arg\min_{h}\left(\mathbf{S}^{\mathbf{R}\{h\}},\mathbf{S^U}\right) \tag{10}$$

Another important concept that must be stressed is that this method does not require a training phase, it just needs a RS for each class.

V. Numerical Results

Four different methods for classifying movements have been tested for comparison: SVM-*OAA*, SVM-*OAO*, DT-C4.5, and *DTW*.
The phone is held by the user in his right hand with the back of the phone facing the palm. Five different users have been tested to collect the movement samples, 4 males and 1 female. All the user have repeated each suggested movement at least 10 times.

TABLE I: MR Confusion Matrix for the SVM-OAO classifier. $C = 1$, $\gamma = 0.1$.
Overall Accuracy: 99.3%.

	AC	AP	AT	C	SW	SR
AC	100	0	0	0	0	0
AP	0	100	0	0	0	0
AT	0	0	100	0	0	0
C	0	0	0	100	0	0
SW	0	0	4	0	96	0
SR	0	0	0	0	0	100

TABLE II: MR Confusion Matrix for the SVM-OAA classifier. $C = 1$, $\gamma = 0.1$.
Overall Accuracy: 94.0%.

	AC	AP	AT	C	SW	SR
AC	97	3	0	0	0	0
AP	0	100	0	0	0	0
AT	0	0	97	3	0	0
C	0	0	0	100	0	0
SW	0	0	30	0	70	0
SR	0	0	0	0	0	100

A. SVM results

There are two possible approaches when using SVM classifiers. Both methods have been described in Section IV-A: *One-Against-All (OAA)* and *One-Against-One (OAO)*. The technique of 10-fold cross-validation has been used for testing both the approaches.

The *OAO* approach is more complex since 15 SVM classifiers had to be trained, one for each combination of 2 classes. This approach is the one that gives the best performance, the overall accuracy is above 99.3%, meaning that it almost always gives the correct classification. It can be seen in Table I reporting the Confusion Matrix (CM). It only fails few times by labeling as *Arm Twist* the 4% of the *Seaweed* movements.

The *OAA* approach requires to train less SVMs, only 1 for each class. Therefore, the overall performance is poorer with respect to the SVM-*OAO*, although it is still good. The accuracy drops to 93.7%. This is due mainly by the *Seaweed* classification correct detections that go from 96% to 70%. This is shown by the CM reported in Table II.

B. C4.5 DT results

Similarly to the SMV tests, the 10-fold cross-validation method has been used to test the Decision Tree classifier. The algorithm used to build the decision tree is the C4.5. It is ruled by 2 parameters: the *ConfidenceFactor* and the *MinNumberObj* per leaf.
After a tuning phase the *ConfidenceFactor* has been set to 0.1 and the *MinNumberObj* per leaf has been set to the 20% of the total number of instances. The performance is poorer than the SVM classifiers, the DT shows an overall accuracy of 76.8%. The classification results are summarized by the CM in Table III.

TABLE III: MR Confusion Matrix for the DT classifier. *ConfidenceFactor*=0.1, *MinNumberObject*=20%.
Overall Accuracy: 76.8%

	AC	AP	AT	C	SW	SR
AC	75.5	0	6.5	13	5.5	0
AP	0	89	6	6	0	0
AT	15.5	5	49	0	31	0
C	14	0	5	71	10	0
SW	0	0	14	0	86	0
SR	0	9.5	0	0	0	90.5

C. DTW results

The DTW does not need a training phase, it just requires one Reference Sequence (RS) for each class. Therefore, for each class one instance has been selected as RS and all the other instances have been used for testing. The results of the tests have been reported in Table IV. The overall accuracy is good although it is still worse than the SVMs'.

TABLE IV: MR Confusion Matrix for the DTW classifier. *W*=50.
Overall Accuracy: 88.8%

	AC	AP	AT	C	SW	SR
AC	99	0	0	0	0	1
AP	0	75	0	0	0	25
AT	0	0	94	0	0	6
C	25	0	0	66	0	9
SW	2	0	0	0	98	0
SR	0	0	0	0	0	100

1) Comparison between Classifiers: This last section a compare the employed classifiers. The evaluation is effectuated by using the same metrics: *TP Rate (TPR)*, *FP Rate (FPR)*, *Precision (P)*, *Recall (R)*, and *F-Score (FS)*.
Table V shows that the SVM is the classifier which provides the best result. It has the highest *TPR*, *P*, *R* and *FS*. As a

TABLE V: A comparison of classifiers proposed for MR.

Classifier	TPR	FPR	P	R	FS
SVM OAO $C = 1, \gamma = 0.1$	99.33	0.13	99.36	99.33	99.35
SVM OAA $C = 1, \gamma = 0.1$	94.54	1.20	95.09	94.00	94.54
C4.5 DT *MinNumObj* = 10% *ConfidenceFactor* = 0.1	76.83	4.68	77.09	76.58	76.84
DTW $W = 50$	88.8	2.27	91.58	88.67	90.10

consequence, it presents the lowest *FPR*. On the other hand, differently from the AR case, the *DTW* provides good results (with a *TPR* around 90%). This is due to the fact that every movement considered significantly differs from the other, so helping the algorithm having a better match between the accelerometer sequences. Finally, C4.5 DT shows the worst result.

VI. Conclusion

In this paper the employment of a smartphone-based platform for remote rehabilitation has been proposed. Among the needed functions of such a platform, this paper evaluates as the accelerometer signal acquired with smartphones can be exploited to reliably recognize patients upper limbs movements. Different classifiers have been compared in terms of recognition accuracy: *i)* Support Vector Machine (SVM), *ii)* C4.5 Decision Tree (DT), and *iii)* Dynamic Time Warping (DTW). The SVM and, in particular, the so called OAO decision modality of the SVM, exhibits very high performance thus making feasible and reliable the remote in-home rehabilitation.

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