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Movement Detection of Human Body Segments

Passive radio-frequency identification and machine-learning technologies.

Movement detection of human body segments is a fertile research topic in human–computer interaction, as well as in medical and entertainment applications. In spite of the fact that most of the current methods to track motion are based on optoelectronic systems and wearable inertial sensors, promising solutions could spring from the application of passive radio-frequency identification (RFID) technology. When the human body’s limbs move within an electromagnetic field radiated by an interrogating antenna, a movement-dependent modulatio
to classify gestures of arms and legs by using only passive and sensorless transponders. The electromagnetic signals, backscattered from the tags during gestures, are collected by a fixed reader antenna and processed by the support vector machine (SVM) algorithm to recognize periodic limb movements and classify more complex random motion patterns. Experimental sessions demonstrated a classification accuracy higher than 80–90%, which is comparable to more complex systems involving active wearable transceivers. The results further indicate that the achievable bit rate is 48 b/min, suggesting that the platform could be used to input coded controls to a gesture-oriented user interface.

**WIRELESS SYSTEM FOR BODY MOVEMENT RECOGNITION**

Movement detection of human body segments plays a key role in several medical applications, such as the diagnosis of sleep diseases and several neurological disorders, the rehabilitation of patients with motor function impairments, remotely monitoring elderly patients or patients who are at risk for heart attacks and epilepsy, and monitoring people in harsh environments, such as firefighters, miners, and astronauts. Currently, the golden standards for motion monitoring applications are optoelectronic marker-based [1] or markerless [2], [5] systems and wireless wearable devices integrating accelerometers, gyroscopes, or other sensor units [3], [4].

In simpler systems with no dedicated sensors [6], motion information is gathered from the electromagnetic signals measured between wireless active transceiver modules placed on the body and an off-body fixed node forming a wireless network. The analysis of the fluctuations of the received signal strength (RSS) due to relative motion of body segments is performed by classification algorithms with the purpose of recognizing specific periodic motor patterns. This setup is capable of recognizing one of eight different motor gestures by analyzing 30 s of received signals.

Active wireless motion classification devices with a local power source, such as a battery, are not suited to be embedded into clothes and garments, especially if the garment will be washed and eventually thrown away. In this context, passive (batteryless) RFID may provide some useful advantages over more assessed active systems. These benefits are: 1) the portability of the system since the reader and the processing unit could be embedded into a small autonomous box, 2) the feasibility of multiuser tracking since the measured RF backscattered signals are digitally signed, and 3) the potential of integrating the motion monitoring system within emerging architectures based on the Internet of Things paradigm [7], which would offer a larger set of services, such as the simultaneous collection of biometric and environmental data.

Wearable RFID tags made up of an antenna and a microchip transponder are interrogated by a remote radio (the reader) through electromagnetic waves. Tags harvest RF power from the impinging field emitted by the reader and reply by modulating the reflected field via digital encoding. When a tag is placed over a limb, as well as the trunk or any other body region, its response will embed movement-dependent amplitude modulation, virtually sensitive to movements, even those that are weak. The study in [8] highlighted that fluctuations of backscattered power from on-body passive tags could provide coarse information about the subject’s state, allowing the researcher to distinguish if the subject is standing or moving, and eventually to estimate the frequency of periodic movements. In [9] and [10], both two-dimensional (2-D) and three-dimensional (3-D) kinematics of body segments/joints during walking are detected by multiple interrogation antennas distributed around the body. So far, passive RFID systems have not been investigated for the purpose of movement classification.

This article investigates batteryless wearable RFID antennas, working in the European ultrahigh frequency (UHF) band (866–868 MHz), for application to the classification of limb gestures when the electromagnetic processing is performed by methods borrowed from machine-learning background that are generally applied to brain–computer interfaces (BCIs) [11], [12] for the recognition of electroencephalographic patterns. Human motor gestures can be similarly related to the changes in both space and time of the power backscattered by wearable tags, thus providing signals that are modulated by the different movements according to specific patterns that can be classified.

**THE RFID SCANNING SYSTEM**

The RFID scanning system (Figure 1) used for all the experiments comprises a UHF reader, ThingMagic M5, connected to a multilayer planar inverted-F antenna (PIFA) with a maximum gain of 5 dB. The antenna is placed 0.9 m from the floor, and it is oriented to radiate a vertical polarized field. The tag and the RF signals to be used for classification deserve a specific discussion.

![Figure 1](image-url)
THE WEARABLE RFID TAG

Since the passive RFID communication link is intrinsically weaker than that of active systems (because of the absence of a local power source), the tag's design represents a critical issue conditioning the overall performance of the classification setup, especially when antennas are to be placed over the high-lossy human body. Indeed, a low-gain antenna could prevent the reader from receiving backscattered signals, therefore jeopardizing the true possibility of classification. In this article, a body-optimized wearable tag is specifically designed [13] as a folded patch with an H-slot impedance tuner (Figure 2). The tag is fabricated over a 3-mm-thick polymeric ethylene propylene diene monomer (EPDM) substrate with dielectric properties of ε_r = 1.21 and σ = 4 · 10^{-5} S/m. The flexibility and the lightness of the EPDM foam make the tag suited for integration in clothes, plasters, wristbands, and various garments with minimal invasiveness for the holders. The RFID microchip transponder connected to the tag is the Impinj Monza 4 IC with a nominal RF input impedance and power sensitivity (e.g., the minimum RF scavenged power that the microchip has to collect before it starts responding to the reader) of Z_{chip} = 13 – j 151 Ω and P_{chip} = −17.5 dBm, respectively. The maximum reading distance, achievable by the maximum 3.2 W effective isotropic radiated power (EIRP) interrogation power allowed by European regulations, was numerically estimated by means of a finite-difference time-domain electromagnetic (EM) tool [14] when placing the tag over a stratified parallelepiped-like model of a human limb. The human limb model consists of a three-layer box: skin and fat (ε_r = 14.5 and σ = 0.25 S/m), muscle (ε_r = 55.1 and σ = 0.33 S/m), and bone (ε_r = 20.8 and σ = 0.33 S/m) [15]. The maximum read distance (along the antenna broadside (frontal) direction) was roughly constant in the anterior half-space with a maximum 

FIGURE 2. (a) The layout of the wearable tag. Size (in millimeters): W_g = 50, L_g = 52, W = 48, L = 50, h = 3, g = 1, p = 12, a = 9, and b = 14. (b) The computer-simulated maximum read region of the tag for 3.2 W EIRP interrogation power, when placed over a limb-like numerical phantom (horizontal plane). The gray slice highlights the shadow region where the read distances are lower than 5 m, due to human tissue losses.

FIGURE 3. (a) The frequency-dependent maximum read distance of the tag prototype placed on the human upper limb, as measured along the tag broadside (frontal) direction. The vertical segments give the data variability in repeated measurements and (b) measurements of the maximum read distance of two tags placed over arms and legs for eight different body postures. All the measurements were performed under the assumption that the reader emits 3.2 W EIRP power.
normal axis) versus the frequency of the RF interrogating signal. Data are obtained by experimental measurements when the tag is placed on a volunteer’s arm, under the assumption that the reader emits 3.2-W EIRP. Three data acquisitions for each frequency were sequentially repeated to investigate the repeatability of the measurement procedure. The error bars in Figure 3(a) show the standard deviation of the data. The variability is mostly due to the stability of the reader electronics and to the unintentional small movements of the volunteer during measurements. The uncertainties produced in the case of taking off and repositioning the tags have recently been demonstrated in [16] to be lower than the resolution given by commercial readers (generally 0.5–1 dB for $P_{\text{m}}$, and 0.81 dB for $P_{\text{BS}}$), and, hence, it should not practically impact the measurements reproducibility.

Thanks to the presence of the ground plane that decouples at the best antenna radiation from the body loss, the measured read distance is nearly stable inside the 860–880-MHz band, therefore, the tag response will have limited sensitivity to possible mismatching effects caused by repositioning the antenna onto different areas of the body. Figure 3(b) summarizes the maximum read distance of the tags over the arms and legs, as estimated by measurements, for eight different positions of the subject that will be considered for the classification problems. From the diagram, it is apparent that the RFID link will be established regardless of the specific body posture, provided that the reader-body distance is smaller than $d = 2\, \text{m}$.

**RFID SIGNALS FOR CLASSIFICATION**

In the experimental examples presented, the reader collects the power backscattered by the tag during body motion. According to the radar formula describing the inverse RFID communication link [15], the EM power backscattered by a passive tag and collected by the reader is given by

$$P_{\text{BS}}(d, \theta, \phi) = P_{\text{in}} \frac{\lambda^2}{(4\pi d)^2} \sigma_T(\theta, \phi) \eta_P(\theta, \phi),$$  \hspace{1cm} (1)

where $P_{\text{in}}$ is the reader input power, $\lambda$ is the wavelength, $\sigma_T$ is the radar cross section of the transponder antenna, and $\eta_P$ is the polarization mismatch between the reader and the tag. It is worth noticing that the $P_{\text{BS}}$ depends on parameters such as the reader–tag distance $d$ and the mutual orientation $(\theta, \phi)$ between the two antennas, which change according to the specific body movement. Therefore, the collected backscattered signals are subjected to an amplitude modulation intrinsically correlated to the motion patterns themselves, and, hence, they can be used to properly feed the classification algorithms.

The measured raw data will hereafter be the normalized backscattered power $p_{\text{BS}} = P_{\text{BS}}/P_{\text{m}}$ that is deduced from the RSS indicator (RSSI) samples collected by the reader through the reader-specific conversion:

$$p_{\text{BS}} = \frac{\text{RSSI} - 117}{1.2} - P_{\text{m}}[\text{dBm}].$$  \hspace{1cm} (2)

**CLASSIFICATION METHOD**

In a machine-learning background, the term “classifier” refers to the procedure of identifying to which category, among a finite set, a data observation belongs. In this context, “categories” have to be intended as a particular type of body movement and the “observations” correspond to the signals backscattered from the tag while the human body moves within the EM field emitted by the reader. Two main paradigms are usually adopted to perform a machine-learning task. The first one, known as supervised learning, needs to first be trained by means of a data set whose belonging class is known a priori. Conversely, unsupervised learning does not require preliminary training to mine the data, instead it heuristically discovers hidden patterns in the observed unlabeled data set. The algorithm applies a specified clustering or grouping to the data sets based on some similarity criteria. Hybrid approaches such as semisupervised learning or reinforced learning schemes based on dynamic “trial-and-error” interactions with the environment are also possible.

This article considers a supervised technique. Each observation is represented by some quantifiable relevant properties, denoted as features, acting as a fingerprint of the event to be classified. During the training phase, the classification algorithm tries to find out the implicit relationship between the observed features and the corresponding categories to build a predictive model capable of correctly classifying unlabeled observations. After the training, the accuracy of the classification model is usually evaluated through testing a data set by comparing known labels with those obtained from the model. Classical $k$-fold techniques are often used for both training and testing. Data sets are randomly split into $k$ subsets, denoted as folds: $(k - 1)$ folds are used for training and the remaining folds are used for validation. The procedure is then repeated $k$ times by sequential rotation until each partition has been used for the test.

The classification process is usually performed by assigning a score to the current measured data representing the relative distance (or similarity) of that data from each trained class. Then, the output label is the one with the lowest (or highest) score. When the scores of the best and the second-best candidates are identical or nearly similar, a classifier may abstain from making a decision, according to a predefined threshold for the difference between the above values. The latter case corresponds to classifiers with a rejection option. The implementation of an abstention rule reduces the probability of misclassifying a measurement at the price of a slight slow down of the overall performance. The block diagram in Figure 4 describes the training and classification procedures for the design and application of a supervised pattern recognition system [17]. The training task comprises data set collection (to be used for both training and testing, described later), the choice of appropriate discriminating features, the selection of the most suitable classification model (templates, decision-theoretic or statistical, syntactic or structural, and neural), the definition of parameters through the training data set, and finally, a performance evaluation. The results of the evaluation may call for the repetition of various steps of the
process until satisfactory results are obtained. Once the prediction ability has been verified, the classifier can be used to categorize new and unlabeled data.

**THE SVM CLASSIFIER**

Among several possible classifiers [11], [17], the SVM algorithm [18] is applied for its detection and classification performance. A SVM is a supervised learning technique originally developed for binary (i.e., two-class) linear classification problems. The algorithm works within the feature space, a multidimensional domain where each event (here the multichannel recording of a limb gesture) is represented by a data point with coordinates corresponding to the event’s features. Feature values are usually normalized so that all the points lie in the unity hypercube of the feature space.

The original formulation of a SVM is based on the fundamental assumption of the linear separability of data points. Two data sets, belonging to classes “A” and “B,” respectively, are linearly separable if there is a hyperplane that divides the space so that points of class A and B lie on opposite sides of it. Under this hypothesis, the algorithm seeks a separation surface described by a hyperplane in a way that all the training data points \( \mathbf{x}_i \) lie on the positive or negative side of the hyperplane, depending on their belonging classes. As a consequence, there will be a vector \( \mathbf{w} \in \mathbb{R}^p \) orthogonal to the hyperplane (the weight vector) and a scalar \( b \in \mathbb{R} \), satisfying the relations:

\[
\mathbf{w} \cdot \mathbf{x}_i - b \geq +\varepsilon \quad \forall \mathbf{x}_i \in \{y_i = 1\}
\]

\[
\mathbf{w} \cdot \mathbf{x}_i - b \leq -\varepsilon \quad \forall \mathbf{x}_i \in \{y_i = -1\},
\]

where \( \cdot \) denotes the dot product and \( b \| \mathbf{w} \| \) is the offset of the hyperplane from the origin along the normal vector direction. Hence, the equations \( \mathbf{w} \cdot \mathbf{x}_i - b = \pm \varepsilon \) will define two boundary hyperplanes delimiting a gap such that there are no training points inside (Figure 5). Without loss of generality, the \( \varepsilon = 1 \) choice is conventionally adopted [18]. The optimal hyperplane is placed in the middle of the gap, and is then identified by the parameter pairs \((\mathbf{w}, b)\) maximizing the distance between those hyperplanes, which can be calculated as \( 2 \| \mathbf{w} \| \).

Practically, to compute the maximum-margin hyperplane, the quantity \( \| \mathbf{w} \| \) needs to be minimized by solving a standard constrained optimization problem:

\[
\min_{(\mathbf{w}, b)} \| \mathbf{w} \|
\]

subject to \( y_i (\mathbf{w} \cdot \mathbf{x}_i - b) \geq 1 \quad \forall i \in \{1, m\}. \)

It is implicit in the method that only support vectors have direct bearing on the optimum location of the decision surface and they would change the position of the hyperplane if removed.

In practice, the separation contour among input data may have a nonlinear shape (Figure 6). In this case, the basic method can be moreover extended to enforce a conformal remapping of the input data from the original space \( \mathbf{x} \) to a

![FIGURE 4.](image)

*(a) The design cycle of the pattern recognition system and (b) the classification procedure to be performed once the classifier has been trained.*

![FIGURE 5.](image)

*The maximum-margin hyperplane in a 2-D feature space \( \mathcal{X} = \{x_1, x_2\} \) for an SVM trained with samples belonging to the two classes. Samples lying on the margin are called support vectors.*

where \( \mathbf{x}_i \) is the \( p \)-dimensional vector that contains the object’s features and \( y_i \) is the label tagging one of the two possible classes.
higher (at limit infinite) dimensional feature space $\mathcal{F}$ where-in the classes become linearly separable. A set of nonlinear functions $\Phi: \mathcal{X} \rightarrow \mathcal{F}$ are applied to perform this projection. Accordingly, the constrain equation (6) of the optimization problem becomes

subjected to \[ y_i(w^T \phi(x_i) + b) \geq 1 \]
\[ K(x_i, x_j) = \phi(x_i)^T \phi(x_j) > 0, \quad (7) \]
where $K(x_i, x_j)$ is a kernel function that corresponds to a dot product in the expanded feature space. There are several types of kernel functions, such as linear, polynomial, exponential, or sigmoid [23]. This article considers the exponential radial basis function (RBF) defined as

\[ K(x_i, x_j) = e^{-\gamma |x_i - x_j|^2}, \quad \gamma > 0, \quad (8) \]

where $\gamma$ is a kernel parameter.

Finally, although the SVM was primarily designed for two-class classification, a multiclass classification is implemented as a multiplicity of binary classification problems that distinguish between 1) one of the labels and the rest (one-versus-all) or 2) between every pair of classes (one-versus-one).

**PERFORMANCE EVALUATION: THE CONFUSION MATRIX**

Denoted by $n$ number of considered classes of motion patterns, a confusion matrix (CM) is a $n \times n$ table that describes the relationships between the estimated and real patterns, e.g., the ability to correctly classify a motor act. The CM is built from the testing data set, which was not used for training, where the correct labels are known. In particular, the CM $(p, q)$ element of the matrix indicates the times that an event of the $p$th class is classified as belonging to the $q$th class. The classification system is as accurate as the CM is diagonal. If a classifier supports abstentions, then an additional column is added and the CM dimensions are extended to $n \times (n + 1)$.

Several performance indicators can be extracted from the CM, such as the accuracy, the information transfer rate (ITR), and the bit rate.

1) **Accuracy**: The accuracy $P$ of a classifier is the percentage of observations that are correctly estimated. It can be easily derived from the CM as the ratio of the sum of the diagonal elements divided by the sum of all the elements.

2) **ITR**: The ITR is a standard measure of communication systems that takes into account both the accuracy and the number of possible outputs of the classifier. In this article, the ITR indicator is used to quantify the amount of information that the RFID-based classification system may convey through motor patterns when using the proposed platform as communication interface. The ITR is derived from the Shannon channel theory, according to Nykopp’s definition [22]. The theoretical upper limit of ITR, referred to as an ideal classifier with an accuracy of 100%, is $\log_2 n$.

3) **Bit Rate**: The ITR provides a measure of the amount of information extracted after each classification. However, it is usually more practical to measure the amount of information that can be extracted in a specific amount of time. The bit rate can be easily computed by dividing the ITR by the time interval between two consecutive classification outputs (expressed in bits per minute).

**DESCRIPTION OF EXPERIMENTS**

Two experimental sessions were conducted with the help of three healthy volunteers with an average age of 26 years. Periodic and single motion patterns are considered in separate experiments. In both sessions, gestures to be executed are communicated to the volunteers by a prerecorded go-signal phrase (e.g., left arm side), which prompts for timing. Instruction labels are collected and stored synchronously with the backscattered signal coming from wearable tags. Using this method, it is easy to keep track of the desired (asked) outputs and the classified ones. Accuracy and error rate are then estimated starting from the CM.

During the experimental sessions, the tags were attached over the body by means of adhesive tape or elastic bands. The volunteers wore tight-fitting clothes, ensuring a stable displacement of the tags on the body segments. Even though small shifts of the tag with respect to the limbs may occur, they are expected to produce only negligible fluctuations of the backscattered power that is mostly governed by the body motion.

It is important to quantify the achievable system performances depending on the choice of the classification features, the number of channels (tags) processed at the same time, the kinds of gestures (legs or arms), the modality of classifier training, and the variability of the subject.

**EXPERIMENT 1: CLASSIFICATION OF PERIODIC MOTOR ACTIVITY**

The purpose of this experiment is to compare the classification capability of batteryless wearable tags with those recently demonstrated for active systems involving true transmitters [6]. The classification of periodic motor patterns concerns the recognition of one of eight predefined kinesiotherapy activities involving limb motions that are typical of a rehabilitation/recovery process [see Figure 3(b)].

1) **Experiment Description**: A couplet of wearable tags are placed on the legs (one on the thigh and one just below the
knee) and on the arms (one on the forearm and one on the upper part of the arm), as shown in Figure 1. Subjects are asked to perform three cyclic movements involving the arms and five involving the legs (see the insets in Figure 7) as in [6]. During the measurements, the activities are performed at a controlled rate of 30 periodic movements/min. During multiple repetitions of the same exercises, the backscattered signals are recorded within 10-s temporal windows. Each of the eight activities is repeated 14 times, therefore, the overall data set consists of 112 instances to be classified, for a total recording of 1,120 s. The reader sampling frequency is 6 Hz (imposed by the RFID reader limitations). Figure 7 shows examples of recorded trace couplets corresponding to the considered motor patterns.

2) Feature Selection and Classification. A classification procedure similar to that described in [6] requires the raw backscattered signals \( p_{BS,1}, p_{BS,2} \) to be compressed into a smaller set of features or attributes acting as a fingerprint for the specific class. The number of the selected features should be as low as possible to avoid overfitting and to reduce computational complexity while achieving discrimination among different classes. A pair of RSSI traces are then identified by a set of six features:

- the standard deviations \( \{\sigma_1, \sigma_2\} \) of the two signals \( p_{BS,1}, p_{BS,2} \)
- the level cross rates \( \{lc(-s_1), lc(+s_1)\} \), \( \{lc(-s_2), lc(+s_2)\} \), e.g., the number of times the backscattered signals cross a given threshold \( s_1 \) with positive slopes.

Since the RSSI values are often unstable and noisy due to environmental interferences and collisions, the collected data need to be preprocessed before feeding the classification process. In particular, solitary nulls are smoothed out by averaging the backscattered power signals \( p_{BS} \) over two neighboring samples. Unlike the benchmark study [6], the proposed platform involves off-body communication links, i.e., the reader antenna is placed far from the body. Therefore, in order to remove the experiment-specific dependance of the collected signals on the distance between body’s barycenter and the reader’s antenna, the power signals are normalized by their averaged value before extracting the classification features. A standard grid-search technique is applied to select the optimal parameters for the RBF kernel [23]. Classification performance is then computed by using a 2-fold cross-validation technique.

**EXPERIMENT 2: CLASSIFICATION OF A SINGLE GESTURE**

The second experiment is designed to investigate the identification of a single motor act within more complex aperiodic sequences. The classification features are now selected with a different procedure, according to the single-trial analysis [12], borrowed from the BCI background. Hereafter, the term “trial” refers to the backscattered signals collected by the reader during a single gesture. For each trial, the backscattered power signals give a space–time matrix \( X_k \in \mathbb{R}^{M \times T} \), where \( M \) and \( T \) are the number of wearable tags (channels) and of time samples (18 in this article), respectively. The considered features for the classification are column vectors \( \tilde{x}_k \) of \( M \cdot T \) length, obtained as a concatenation of the columns of \( X_k \). These features are richer than those considered for the classification of periodic motion patterns. A greater number of features mean that more data are required to train the classifier. Contiguous trials are separated by 3-s intervals. It is worth noting that even if each movement occurs every 3 s, it is executed at the natural speed so that each motor act (forward and backward) lasts about 1 s. About 1 s is spent at the beginning of the trial for the prerecorded go signal and the comprehension by the volunteer. Another second of recovery time is reserved after the motor act to prevent the next command from occurring while the previous action is still in progress, which would confuse the subject. Abstentions are also considered, meaning that no decision is taken if the confidence level of the classification does not exceed a certain threshold.

First, eight classes of motor patterns are analyzed by processing two data sets involving, in separate experiments, four arm and four leg motions. This is done to see if gestures of both limbs are classified with the same performances. In particular, there are 25 instances for each motor act, distributed in a pseudorandom sequence composed of 100 movements. The details of patterns and of typical backscattered signals are shown in Figure 8. Then, another recording session composed of 400 movements, equally distributed, among the eight classes, is acquired to investigate the achievable bit rate by considering the complete set of the movements of both legs and arms at the same time. The training activity is independently repeated for each volunteer.

**RESULTS**

**EXPERIMENT 1: CLASSIFICATION OF PERIODIC MOTOR ACTIVITY**

Figure 9 shows the CM corresponding to the considered arm [Figure 9(a)] and leg activities [Figure 9(b)], in both separate tests as well as aggregated into a unique data set [Figure 9(c)]. It is apparent that the matrices are mostly diagonal with an accuracy of 97.6% and 97.1%, respectively, for arm and leg movement recognitions.

The achieved communication performance in terms of gesture data rate is \( ITR = 1.5 \) b/symbol (bit rate 9 b/min) for upper limb activities and of \( ITR = 2.2 \) b/symbol for lower limb activities (bit rate 13.2 b/min). When the global data set is considered, the accuracy is reduced to 91%, whereas the ITR increases to 2.6 b/symbol (bit rate 15.6 b/min). It is worth noticing that an increase in the number of motor tasks may result in an improvement of the system communication capability at the cost of a slight accuracy reduction due to the widening of the classification problem size.

**ACCURACY VERSUS A REDUCED NUMBER OF TAGS**

The quality of the classification is expected to be potentially affected by the number of tags and their position over the body. Figure 10 shows the achievable classification performances when a single tag per limb is used instead of two. In this case, each motor pattern in Figure 7 is scanned...
FIGURE 7. The examples of 10-s-recorded traces of the powers backscattered by the couplets of tags over the arms and legs during the (a)–(h) eight periodic motor patterns sketched in the insets. An example of level cross-rate detection is visible in (c), where the filled circles indicate the higher level cross rate \( \text{lcr}(\mu_1 + \sigma_1) \) and the empty circles indicate the lower level cross rate \( \text{lcr}(\mu_1 - \sigma_1) \).
through a single backscattered power trace and there are only three corresponding features, e.g., \( \{ \sigma, lcr(-s_1), lcr(+s_1) \} \). The CMs are now spread outside the main diagonal corresponding to a slight reduction in the classification accuracy with respect to the experiments with two tags per limb. The classification of motor data sets originated by arm motions is likely to benefit from the placement of the single tag over the forearm (92.9% accuracy versus 85.7%) since this body segment produces a larger motion than the arm and, hence, generates a broader dynamic range of the backscattered power. Concerning leg motions, the classification accuracy (84.3%) looks rather insensitive to the position of the single tag. In regard to the communication ability of the system, the ITR is reduced to 1.2 b/symbol (bit rate 7.2 b/min) for the arm position corresponding to the best performance and ITR = 1.6 b/symbol (bit rate 9.6 b/min) for a single tag placed over the leg regardless of the specific position.

**EXPERIMENT 2: CLASSIFICATION OF A SINGLE GESTURE**

Similar to the previous experiment, two distinct data sets (one for each limb) are initially considered. The SVM classifier is trained by both the 2- and 10-fold validation methods in order to assess the effects of the training data set size. CMs can be observed in Figure 11.

Performances are now different, depending on the kind of limb (legs or arms) even on the training foldings. In particular, the accuracy is better in the classification of arm motions, while errors are observed for the leg motions with a non-negligible number of abstention (unclassified) cases. As expected, moving from a 2-fold to 10-fold validation method, the accuracy improves at the expense of a greater number of trials required to train the classifier. It should be noted that the bit rate increases because of the reduced observation time necessary to classify a single movement: bit rates of 40 and 31 b/min are obtained for the 10-fold training procedure for the upper and lower limbs, respectively. The details about accuracy and ITR are shown in Table 1.

It has been verified that, without the abstention rule, the accuracy percentage generally increases (for instance, 78–87% in the case of legs, \( k = 10 \)-fold) at the expense of the error rate from 4% to 13% and of the bit rate from 31 b/min to 27 b/min.

The training procedure plays a key role in improving the accuracy.

The whole data set of 400 trials and eight movements is then used to investigate the dependence of the classification accuracy across human variability. Because of the unique biomechanic characteristics of a person, different patterns are generally recorded for different subjects, even if they are performing the same motor act (Figure 12). The 10-fold validation method is applied since it provides better results, as shown in the previous test.

The bars in Figure 13 show the results of the experiments (the aggregated percentages are shown in Table 2) where the individual variability of responses is clearly visible. The average accuracy is 82.5%, while the average error rate is 5.4%. The overall bit rate is 47.1 b/min.

It is worth noting that subject number three correlated with the best classification accuracy, was more skilled with the execution of the motor patterns, and he was able to correctly execute all requested movements during the training phase. On the contrary, subjects number one and number two, which showed similar performances, were sometimes doubtful.

![FIGURE 8. An example of backscattered signals emitted by two tags over (a) the arms and (b) legs for a random sequence of the four motor patterns described in the upper part of the figure.](image)
about which movement to execute after the request command and even made some wrong movements during the training recording session, potentially compromising the effectiveness of the training task. Nevertheless, the corresponding accuracy is still acceptable (around 80%) suggesting that the proposed classification method is fault tolerant for some mistakes that may occur during the training phase.

Moreover, it can be observed that, regardless of the subject, the most challenging motor pattern to be recognized is number five (shown in Figure 12), which involved a wide extension of the leg. For the sake of completeness, it is worth reporting that poor results are obtained in the case of cross-training testing, i.e., by using the training data of \( n \)th subject to classify the motion of \( m \)th one (with accuracy less than 30%).

**COMPARISON WITH WIRELESS ACTIVE SYSTEMS**

The performance of the proposed RFID system in the classification of single gestures can be compared with those of the active setup described in [6], wherein the same experiments used in this article were originally performed.

Unlike the proposed RFID scanning system that involves an off-body communication link, i.e., the RSSI of the tag is measured by a reader placed far from the body, the active configuration in [6] employed an on-body network. In [6], a transmitting module, placed at the center of the waist, periodically sent a beacon packet at a fixed power level. Receiving active motes were attached over the limbs and received the packet from the reader, estimated the RSS, and sent this information to an off-body gateway node.

The accuracy of the active network can be roughly estimated to be 90% (from the manual processing of the CM of...
Figure 5 in [6] for both arm and leg movements that were classified as two separate data sets. The RFID-based system produced an accuracy of 97.6% and 97.1%, for arm and leg movements, respectively. For the overall data set, including both arm and leg exercises, the accuracy achieved by the RFID system was 91%, which is still comparable to that of the active system despite of the bigger size of the classification problem in the RFID experiment.

Some additional remarks concern the size of the training data set. In [6], each movement was repeated 50 times and each exercise lasted for 30 s (for an overall recording session of 200 min). However, in this article, the volunteers were asked to perform 14 repetitions of the same activity lasting 10 s for a total recording session of 18 min. In practice, the RFID system required a faster training of the classifier.

Finally, better communication capabilities have been experienced with the passive RFID system. Even under the ideal assumption that the active system is able to recognize one of eight movements with an of accuracy 100%, the corresponding ITR would be just 6 b/min versus ITR > 45 b/min of the RFID system due to the longer time needed to recognize each motor task (30 s versus 10 s).

CONCLUSIONS
Experimental tests demonstrate the feasible application of wearable passive RFID tags, placed onto the human body to classify periodic movements and to recognize single gestures occurring within random sequences. The SVM classification method allows for classification of periodic patterns with an accuracy comparable to that of active devices [6], with a shorter
training and better performance in information transfer. Finally, even more complex aperiodic motion sequences can be successfully classified by the RFID-based system with an average accuracy of more than 80%.

In all the cases, the classification of leg movements turns out to be more challenging than those of the arm due to the broader motor dynamic that may produce poor values of backscattered power close to the sensibility of the reader’s receiver. A single tag per limb is enough for the discrimination of periodic movements, while two tags are required to classify single acts. Tests indicate that the training procedure plays a key role in improving the accuracy. However, this training procedure is dependent upon the subjects participating and, hence, at least for the time being, ad personam training is required.

In spite of the fact that more accurate devices are currently available to measure trajectories of special markers

**FIGURE 11.** The CMs for the multiclass problem with an SVM concerning arm and leg motions. (a) and (b) Results for 2-fold validations. (c) and (d) Results for 10-fold validations. Z-axis labels denote the normalized probability of occurrence ($\hat{P}_{oc}$) that one movement is assigned to a specific class.

**TABLE 1. THE PERFORMANCE OF THE SVM APPLIED TO THE RANDOM SEQUENCES OF ARM AND LEG MOVEMENTS.**

<table>
<thead>
<tr>
<th></th>
<th>2-Fold</th>
<th>10-Fold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arm Accuracy (%)</td>
<td>86</td>
<td>98</td>
</tr>
<tr>
<td>Leg Error rate (%)</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>ITR (b/symbol)</td>
<td>1.7</td>
<td>2</td>
</tr>
<tr>
<td>Bit rate (b/min)</td>
<td>35</td>
<td>40</td>
</tr>
</tbody>
</table>
FIGURE 12. The eight-class experiments. (a) The set of performed limb movements and (b) signals acquired for three volunteers.
attached on the body, producing clinically relevant data (e.g., the frequency and amplitude of a tremor), the capability of correctly identifying predefined movements with a portable, lightweight, easy-to-use, and cheap device may represent a valid option in several contexts.

1) **Rehabilitation**: RFID technology can be used to quantify the number of exercises that have been performed by a patient, and when integrated into a smartphone, a physiotherapist can immediately monitor the patient’s performance and assess the quality of the recovery process remotely. Moreover, other physical signals, such as body or environmental temperature, can be simultaneously collected by the same system if new-generation microchips with digital sensing capabilities are embedded within the wearable tags.

2) **Human–Computer Interaction**: The proposed platform can be used to input coded controls to a body gesture-oriented user interface conceived for impaired people as it is capable of achieving a bit rate up to 54 b/min, which means making a binary decision (e.g., to command a switch).

3) **Patients Activity Monitoring**: The system capabilities can be easily extended to noninvasively recognize accidental falls, epileptic seizures, or even behavioral anomalies (e.g., repeated unnatural and stereotyped movements) that could precede critical pathological phenomenologies.

However, many issues still remain. The minimum number and positions of wearable tags need to be investigated depending on the set of motions to be recognized. The performance of the RFID platform needs to be analyzed in the case of a richer set of motor classes, including the combined motion of two limbs and the concurrent rotation of the torso. Moreover, all the experiments presented here refer to a fixed reader-tag system. It is, therefore, of great interest to further investigate human motions, including walking, and to evaluate the maximum range where the classifier will continue to work correctly. It is expected that the correct classification of more complex and combined motion patterns will require the collection of a bigger training data set, including the combination of multiple activities at the same time, which would require a longer training time.

The described tests have been performed by means of offline data processing, but real-time applications can be easily implemented and an example can be observed in [24].

The last remark concerns EM power issues. Since the continuous improvement in the microchip sensitivity promises a

### TABLE 2. THE EIGHT-CLASS EXPERIMENTS: AGGREGATED RESULTS.

<table>
<thead>
<tr>
<th>Subject One</th>
<th>Subject Two</th>
<th>Subject Three</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy (%)</td>
<td>76.8</td>
<td>80</td>
<td>90.7</td>
</tr>
<tr>
<td>Error rate (%)</td>
<td>8.7</td>
<td>5.5</td>
<td>2</td>
</tr>
<tr>
<td>ITR (b/symbol)</td>
<td>2.1</td>
<td>2.3</td>
<td>2.7</td>
</tr>
<tr>
<td>Bit rate (b/min)</td>
<td>42</td>
<td>46</td>
<td>54</td>
</tr>
</tbody>
</table>

**FIGURE 13.** The eight-class experiments: percentages of the (a) correct, (b) wrong, and (c) unclassified events for the eight different activities performed by three subjects.
power halving every one to two years, it will be soon be feasible to pack the full hardware and software motion classification modules inside a smartphone-like device, therefore enabling the highest level of customization and portability.

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