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Improved Metric for Classification of Nearby Reaching Targets: A Distance-Weighted Accuracy Approach

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Abstract:

Accurate classification of reaching targets is essential for upper-limb prosthesis control, rehabilitation robotics, and human–robot interaction. Conventional accuracy assumes equal misclassification costs and therefore does not distinguish between errors involving spatially adjacent and distant targets. We propose a spatially informed distance-weighted accuracy metric that assigns misclassification costs according to the normalized Euclidean distance between intended and predicted targets, with greater penalties for more distant errors. We first demonstrate the utility of the proposed metric using synthetic confusion matrices with identical conventional accuracy (33.3%) but distinct spatial error patterns (near, far, and random). While conventional accuracy remained 33.3% for all three cases, distance-weighted accuracy yielded scores of 77%, 33.3%, and 49%, respectively with the weighting parameter (ω) set to 1. The proposed metric was also evaluated on a real-world EEG-based reaching-target classification task using Quadratic SVM (QSVM) and Gaussian SVM (GSVM) classifiers. Performance was assessed using five repetitions of two-fold cross-validation (5×2 CV), and classifier differences were evaluated using the combined 5×2 CV F-test. Conventional accuracy was 48.90 ± 6.33% for QSVM and 31.30 ± 8.24% for GSVM, with a statistically significant difference (p = 0.00476). Using the proposed distance-weighted accuracy with $\omega = 1.5$, QSVM achieved 87.12 ± 1.75%, compared with 75.93 ± 9.44% for GSVM. however, this difference was not statistically significant (p = 0.197). These findings demonstrate that the proposed metric provides a complementary, distance-aware assessment of classification performance by accounting for the physical distances between predicted and true classes beyond conventional exact-match accuracy.

Keywords:

reaching target classification, upper-limb prosthesis control, spatially weighted accuracy, performance evaluation metrics, misclassification cost

1. Introduction

Accurate prediction of reaching targets is critical for enhancing the control of upper-limb prostheses, assistive robotics, and rehabilitation devices. This capability directly empowers individuals with motor impairments to perform essential activities of daily living (ADLs) [1-5]. To achieve this prediction, researchers employ classification algorithms, spanning traditional methods to deep learning models, trained on diverse physiological and kinematic data. Common signal sources include electroencephalography (EEG) [6], electromyography (EMG) [7-11], inertial measurement units (IMUs) [1], or increasingly, multimodal approaches integrating eye tracking, contextual cues, and other sensors [5, 12]. Beyond prosthesis control, precise target prediction is equally vital for rehabilitation robots, enabling optimal trajectory planning between movement initiation and endpoint [5].

The evaluation of classifier performance in most prior reaching target prediction studies has relied heavily on conventional accuracy metrics [6-11]. While simple and widely adopted, a significant limitation of this approach is its underlying assumption: all misclassification errors incur equal cost, irrespective of the

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spatial relationship between the intended and predicted targets. This uniform cost assumption is often unrealistic in practical applications. In fields like medical diagnosis, misclassification costs demonstrably vary (e.g., false negatives in cancer detection carry far higher consequences than false positives) [13-15]. Crucially, within the specific context of reaching target prediction, errors are not uniformly distributed. Due to inherent similarities in the underlying neural activation patterns (EEG) or muscle synergies (EMG) [6, 7] or kinematic profiles [1], classifiers exhibit a pronounced tendency to confuse spatially adjacent targets. For instance, [6] documented frequent misclassifications between neighboring targets in a four-target paradigm, while [7] observed declining conventional accuracy as target positions converged spatially. Although studies like [5] have incorporated additional metrics (e.g., region prediction accuracy), a fundamental limitation persists: existing evaluation frameworks inherently treat all misclassifications equally, failing to account for the critical dimension of spatial proximity between targets.

This uniform cost assumption fails to capture the spatial context of reaching tasks and can lead to misleading assessments of a classifier's practical utility in real-world control scenarios. A misclassification to a nearby target position is clinically and functionally preferable to one assigned to a distant position, yet standard metrics penalize both identically. Consequently, classifiers achieving identical conventional accuracy can exhibit fundamentally different – and clinically significant – misclassification behaviors: one might predominantly confuse adjacent targets, while another makes errors distributed across distant locations. To bridge this gap and enable a more meaningful performance assessment, we propose the application of a spatially weighted accuracy metric, adapting the concept introduced in [16] for the specific demands of reaching target classification. This metric explicitly incorporates the Euclidean distance between the true target and the misclassified target. Errors to near positions incur lower penalties, while errors to far positions are penalized more severely. This approach better reflects the practical usability of classification algorithms in prosthetic or robotic control, where a "near-miss" prediction may still yield a functionally acceptable outcome, whereas a distant error likely results in failure.

The primary objective of this study is to rigorously demonstrate the necessity and utility of spatially aware evaluation metrics in reaching target classification. We hypothesized that such metrics may provide a more nuanced and functionally relevant assessment of classifier performance than conventional accuracy, and that they may help differentiate classifiers according to the spatial severity of their errors, potentially revealing differences not captured by raw accuracy alone. To test this hypothesis and illustrate the practical impact of the weighted metric, we employ a two-stage validation: (1) We generate three synthetic confusion matrices possessing identical conventional accuracy but exhibiting distinct spatial misclassification patterns. (2) We apply the proposed metric to evaluate two trained classifiers with different conventional classification accuracies and examine how accounting for physical distances between predicted and true target classes provides complementary insight into their performance. By comparing conventional accuracy with the proposed distance-weighted accuracy, we demonstrate how distance-based weighting distinguishes classification errors according to their spatial severity, penalizing errors involving more distant targets more strongly and providing a more functionally relevant assessment of classification performance. The classifiers are evaluated using repeated 5×2 cross-validation, and their performance differences are assessed using the Combined 5×2 CV F-test [17].

The main contribution of this study is the development and evaluation of a task-specific modified accuracy metric for reaching-target classification that accounts for the spatial severity of classification errors. The proposed framework extends conventional accuracy by distinguishing misclassifications according to the distances between intended and predicted target positions. Its main contributions are threefold. **First, a task-specific spatial cost matrix is introduced to quantify misclassification severity based on the Euclidean distances between target positions. Second, a parameterized cost function is incorporated to allow the relationship between spatial distance and misclassification cost to be adjusted for**

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different task requirements. Three weighting parameter values are examined in the EEG-based classification experiment to assess the sensitivity of the proposed metric to parameter selection, while an additional parameter value is used in the synthetic confusion-matrix analysis to demonstrate the metric's ability to distinguish spatially different error patterns. Movement-phase-dependent cost adaptation is left for future work. **Third, the spatial costs are incorporated into a modified accuracy metric normalized relative to a task-defined worst-case misclassification cost**, providing a complementary assessment of classifier performance that can be computed directly from a confusion matrix.

The remainder of this paper is structured as follows: Section 2 details methodology of distance weighted accuracy computation. Section 3 evaluates the proposed metric with comparing classifiers performance using both conventional and modified accuracy metrics and analyzing the confusion matrices. Section 4 discusses the implications of our findings. Finally, Section 5 describes conclusion including study limitations, and suggests directions for future work.

2. Methodology

While conventional accuracy measures overall classification rate, it assigns equal cost to all misclassifications, irrespective of spatial proximity between targets. For reaching target prediction, however, misclassifying a target as a spatially adjacent location is functionally less detrimental than misclassifying it as a distant location. To incorporate this essential spatial sensitivity and penalize distant errors more severely, we employ a modified accuracy metric where the cost of misclassifying a true target *i* as predicted target *j* is weighted by the normalized Euclidean distance δ_{ij} between their positions. The computation of this distance-weighted accuracy metric involves two primary steps:

1. Misclassification Cost Matrix: The pairwise Euclidean distance between all target positions is computed in this step. This distance then serves as the basis for the misclassification cost matrix.

2. Weighted Accuracy Calculation: the overall modified accuracy using the defined cost matrix and the theoretical worst-case misclassification cost for normalization is computed. This aggregates the costs of misclassified instances relative to the maximum possible cost.

2-1- Misclassification Cost Matrix Definition

The first step in computing the misclassification cost is to calculate the pairwise distances between targets using their 3D Cartesian coordinates. The Euclidean distance d_{ab} between targets a and b is:

$$d_{ab} = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2 + (z_a - z_b)^2} \quad (1)$$

To account for anatomical differences in upper extremity length, target positions were scaled for each participant. The maximum inter-target distance for each subject was determined, and all subsequent inter-target distances were normalized relative to this subject-specific maximum (Fig. 1).

$$\delta_{ab} = \frac{d_{ab}}{d_{\max}} \quad (2)$$

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The cost C_{ab} of misclassifying a trial from true target *a* as target *b* can be defined with multiple functions like linear, power-law based and so on. These functions have to meet three following conditions respect to distance:

- they have to be non-decreasing function if $d_{ab} \le d_{cd}$ then $C_{ab} \le C_{cd}$
- they have to be approximately 1 for the farthest distance of targets $C_{ab}(\delta_{\max}) = 1$
- they have to be 0 for the target position $C_{ab}(0) = 0$

Three types of cost function are proposed in this paper:

- linear
- normalized rational
- saturating power

The linear cost function is a linear function with respect to the normalized distance. It satisfies both the non-decreasing property and the boundary conditions, and is defined as follows:

$$C_{ab} = \delta_{ab} \tag{3}$$

The cost function attains a value of zero at the target position and monotonically increases to one as δ_{ab} reaches the maximum inter-target distance.

The normalized rational function, which also satisfies the two aforementioned conditions, is defined in terms of δ_{ab} as:

$$C_{ab} = \frac{(1+\lambda)\delta_{ab}}{(1+\lambda\delta_{ab})} \qquad \lambda \in (-1, \infty) \tag{4}$$

Here, λ is a weighting parameter, and the cost function reduces to the linear cost function when $\lambda = 0$. The function attains a value of zero when the normalized distance $\delta_{ab} = 0$, and increases monotonically with δ_{ab}. It reaches its maximum value, $C_{ab} = 1$, when the pair *(a,b)* is separated by the maximum normalized distance, i.e. $\delta_{ab} = 1$.

The saturating power function, like the other two functions, satisfies the non-decreasing property and the boundary conditions, and is defined as:

$$C_{ab} = 1 - (1 - (\delta_{ab})^{\omega})^{\frac{1}{\omega}} \quad \omega \in (0, \infty) \tag{5}$$

Where, ω is a weighting parameter, and the cost function reduces to the linear cost function (as does the normalized rational cost function) when $\omega = 1$. For very small values of δ_{ab}, the function takes values close to zero, and it monotonically increases to reach one when $\delta_{ab} = 1$.

Other cost functions can be defined depending on the specific nature of the problem. Each misclassification cost function generates a corresponding cost matrix, which enumerates the costs for all possible pairwise target misclassifications in the reaching movement classification task. Table 1 provides an illustrative example of a cost matrix for the prediction of four reaching targets.

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2-2- Weighted Accuracy Computation

To evaluate reaching target prediction under asymmetric spatial penalties, we define a cost-sensitive accuracy metric. Given a misclassification cost matrix **C** (Table 1), where the costs reflect the spatial distances between targets, the modified accuracy is computed as:

$$Modified\ accuracy = 1 - \frac{Total\ incurred\ cost}{Worst\ case\ cost} \tag{6}$$

Where the worst-case denominator corresponds to systematic misclassification of each true target to its maximally distant position (formal definition in (Eq. 1, Eq. 2)). The metric scales performance relative to the severity of spatial error.

$$Modified\ accuracy = 1 - \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}(C_{ij} * n_{ij})}{\sum_{i=1}^{N}(C_{i\max} * n_i)} \tag{7}$$

in which n_{ij} is number of trials of true class *i* misclassified as class *j*, C_{ij} is cost of misclassifying true class *i* as class *j* (from (Eq. 3- Eq. 5)), $C_{i\max} = \max_{k,k\neq i}(C_{ik})$ is cost of misclassifying true class *i* as its geometrically farthest possible target *k*, n_i is total number of trials for true class *i* and *N* is number of targets.

This metric ranges continuously from zero to one. A value of one indicates perfect classification. A value of zero corresponds to the worst-case scenario, in which every trial of true class *i* is misclassified as the farthest possible target *k* that maximizes C_{ik} .

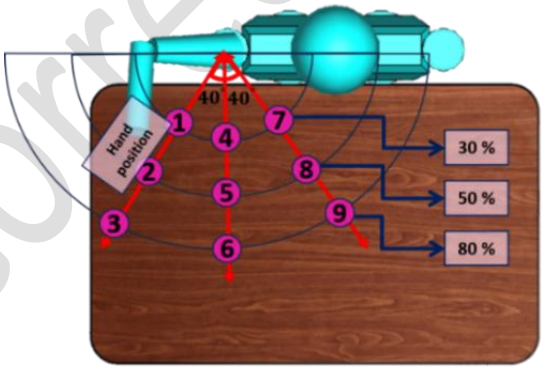


Fig. 1. Experimental setup for the reaching task, with targets positioned at 30%, 50%, and 80% of the maximum reachable distance of the subject.

Table 1. Cost matrix Showing Pairwise Misclassification Costs in A Four-Target Reaching Prediction Task

Target position class	Predicted Target position class			
	1	2	3	4
1	0	C_{12}	C_{13}	C_{14}
2	C_{21}	0	C_{23}	C_{24}

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Target position class	Predicted Target position class			
	1	2	3	4
3	C_{31}	C_{32}	0	C_{34}
4	C_{41}	C_{42}	C_{43}	0

3. The results and discussion

3-1- Results

In this section, we evaluate the performance of both conventional accuracy and the proposed distance-weighted accuracy metric (Eq. 7). First**,** we validate the metric's ability to discriminate between distinct error patterns using manually constructed confusion matrices possessing identical conventional accuracy but differing spatial misclassification distributions. Subsequently**,** we demonstrate its practical utility by applying both metrics to evaluate classifiers trained on a real-world EEG-based reaching target prediction task.

The first step in the modified accuracy computation is the selection of a misclassification cost function. The cost functions under consideration are examined for different weighting parameter values as a function of the normalized distance (Fig. 2). All functions reach a value of one at the maximum distance from the target and zero at the target position. Both the normalized rational and saturating power cost functions reduce to the linear cost function when $\lambda = 0 \,\&\, \omega = 1$ and they exhibit different patterns of variation as the prediction moves away from the target point.

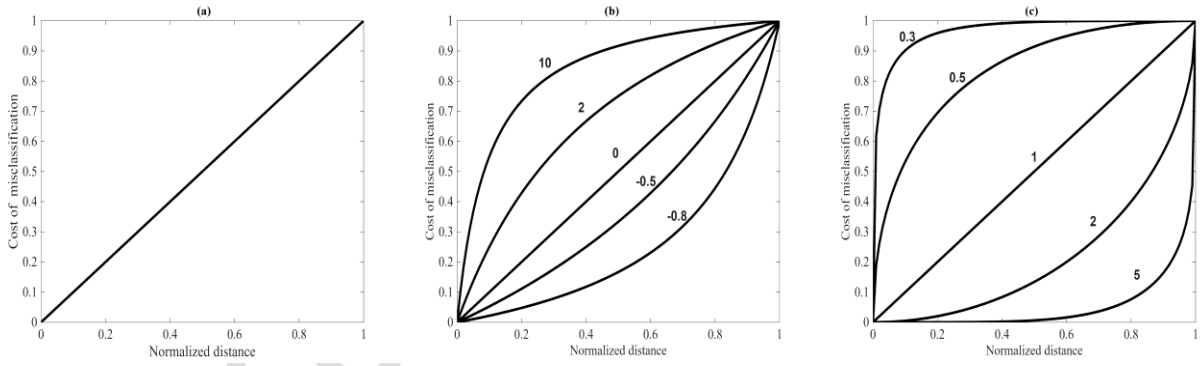


Fig. 2. Cost functions based on normalized distance for different values of the parameter λ and ω: (a) Linear, (b) Normalized rational, and (c) Saturating power.

Accurate prediction of the intended target during reaching movements becomes increasingly important as the hand approaches the potential target locations, particularly when discriminating between spatially adjacent targets. From this perspective, the cost associated with target misclassification may depend on the phase of the reaching movement, since precise target discrimination becomes increasingly relevant as the movement progresses.

To represent this potential temporal variation in misclassification cost, we considered the saturating power cost function (Eq. 5). The weighting parameter ω controls the shape of the distance-to-cost relationship and therefore determines how strongly spatial misclassifications are penalized. Larger values of ω yield lower costs for spatial errors that are substantially below the maximum distance, whereas smaller values of ω produce higher costs for the same errors (Fig. 3). Consequently, a phase-dependent adjustment of ω could

theoretically be used to assign relatively lower spatial penalties during the earlier phase of the movement and progressively higher penalties as the hand approaches the target.

The proposed modified accuracy metric was first evaluated using synthetic confusion matrices with a single weighting parameter value ($\omega = 1$). Its results were compared with those of weighted Cohen's kappa, calculated using the same spatial cost matrix. The metric was then applied to real EEG-based reaching-target classification data using $\omega = 0.3, 1.5 \text{ and } 5$. Dynamic adjustment of the weighting parameter according to the movement phase was not implemented and remains a topic for future research.

3-2- Engineered Confusion Matrices Demonstrating Accuracy Limitations

We generated three confusion matrices for a four-class custom reaching target classification task (15 trials per class; Fig. 4). Table 2 illustrates the first matrix, characterized by misclassifications between proximal targets (e.g., positions 1→2). Table 3 shows the second matrix with misclassifications between distal targets (e.g., positions 2→4), while Table 4 presents randomly distributed misclassifications generated via MATLAB simulation. Despite these distinct error patterns, all matrices share an identical standard classification accuracy of 33.3%.

3-3- Spatially-Derived Cost Matrix Formulation

The maximum inter-target distance, $d_{24} = 33\text{cm}$, was identified from the spatial configuration of targets (Fig. 4). All pairwise inter-target distances d_{ij} were normalized by this maximum distance, yielding normalized distances δ_{ab} (Eq. 1, Eq. 2). The saturating power misclassification cost was then computed for each (i,j) pair, where $\omega = 1$. This cost function assigns higher penalties for misclassifying widely separated targets, reflecting their relative spatial dissimilarity. The resulting cost matrix for the reaching target classification task is presented in Table 5.

3-4- Cost-Sensitive Performance Evaluation

The total misclassification cost for each classifier was computed by performing element-wise multiplication between the corresponding confusion matrix (Tables 2-4) and the misclassification cost matrix (Table 5), followed by summation of all elements. The worst-case classification cost was similarly derived using a specially constructed confusion matrix where all predictions maximized cost (Table 6). The total cost for each classifier was calculated as:

$$L_k = \sum_{i=1}^{N} \sum_{j=1}^{N} C_{ij} * n_{ij}^{(k)} \quad (8)$$

Where C_{ij} represents the cost of misclassifying target i as j, and $n_{ij}^{(k)}$ denotes the error counts in confusion matrix k. The worst-case cost L_{wc} was computed analogously using Table 6. The results of spatially-weighted accuracy calculation are as follows:

1. **Near error pattern (Table 2):**

$L_1 = 12$

Component Breakdown:

$\text{Class1: } C_{12}n_{12} + C_{13}n_{13} + C_{14}n_{14} = 1.5$

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$\text{Class}\,2: C_{21}n_{21} + C_{23}n_{23} + C_{24}n_{24} = 1.5$

$\text{Class}\,3: C_{31}n_{31} + C_{32}n_{32} + C_{34}n_{34} = 4.5$

$\text{Class}\,4: C_{41}n_{41} + C_{42}n_{42} + C_{43}n_{43} = 4.5$

2. Far error pattern (Table 3):

$L_2 = 35.1$

Component Breakdown:

$\text{Class}1: C_{12}n_{12} + C_{13}n_{13} + C_{14}n_{14} = 9$

$\text{Class}\,2: C_{21}n_{21} + C_{23}n_{23} + C_{24}n_{24} = 10$

$\text{Class}\,3: C_{31}n_{31} + C_{32}n_{32} + C_{34}n_{34} = 6.1$

$\text{Class}\,4: C_{41}n_{41} + C_{42}n_{42} + C_{43}n_{43} = 10$

3. Random error pattern (Table 4):

$L_3 = 26.59$

Component Breakdown:

$\text{Class}1: C_{12}n_{12} + C_{13}n_{13} + C_{14}n_{14} = 11.1$

$\text{Class}\,2: C_{21}n_{21} + C_{23}n_{23} + C_{24}n_{24} = 2.21$

$\text{Class}\,3: C_{31}n_{31} + C_{32}n_{32} + C_{34}n_{34} = 7.13$

$\text{Class}\,4: C_{41}n_{41} + C_{42}n_{42} + C_{43}n_{43} = 6.15$

4. Worst-case scenario (Table 6):

$L_{wc} = 52.65$

Computed as:

$C_{14}n_1 + C_{24}n_2 + C_{32}n_3 + C_{42}n_4 = 15(0.9 + 1 + 0.61 + 1) = 52.65$

Finally, the distance-weighted accuracy for each classifier was computed as:

$$\text{Modified accuracy of near error pattern} = 1 - \frac{12}{52.65} = 0.77$$

$$\text{Modified accuracy of far error pattern} = 1 - \frac{35.1}{52.65} = 0.33$$

$$\text{Modified accuracy of random error pattern} = 1 - \frac{26.59}{52.65} = 0.49$$

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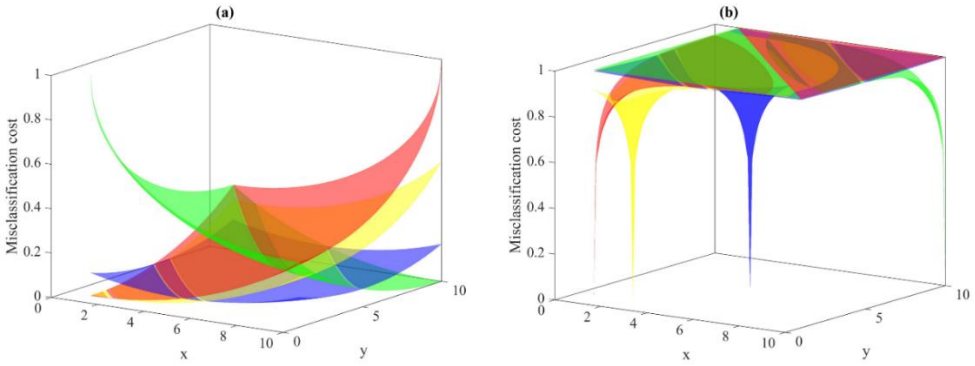


Fig. 3. Saturating power cost function for targets located at (1,1), (2,2), (5,5), and (10,10) on the x–y plane: (a) with $\omega = 2$ representing early movement and (b) with $\omega = 0.3$ representing movement completion.

To complement the proposed modified accuracy, weighted Cohen's kappa was calculated for the three synthetic confusion matrices using the same spatial cost matrix presented in Table 5 ($\omega = 1$). Weighted Cohen's kappa was computed as:

$$k_{weighted} = 1 - \frac{D_o(\omega)}{D_e(\omega)} \tag{9}$$

where $D_o(w)$ and $D_e(w)$ denote the observed and expected weighted disagreements, respectively. The expected disagreement was determined from the marginal distributions of the true and predicted classes.

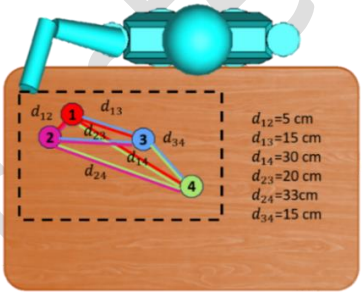


Fig. 4. A reaching target classification task with four asymmetrically positioned targets on the x-y plane. Distances between targets are denoted as *d* (in centimeters).

Table 2. Confusion Matrix with Misclassified Instances Positioned Near the Reaching Targets

Target position class	Predicted Target position class			
	1	2	3	4
1	5	10	0	0
2	10	5	0	0
3	0	0	5	10
4	0	0	10	5

Table 3. Confusion Matrix with Misclassified Instances Positioned Far from Reaching Targets

Target position class	Predicted Target position class			
	1	2	3	4
1	5	0	0	10

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Target position class	Predicted Target position class			
	1	2	3	4
2	0	5	0	10
3	0	10	5	0
4	0	10	0	5

Table 4. Confusion Matrix with Misclassified Instances Positioned Randomly Relative to Reaching Targets

Target position class	Predicted Target position class			
	1	2	3	4
1	1	2	0	12
2	4	9	1	1
3	3	8	2	2
4	3	3	1	8

Table 5. Misclassification Cost Matrix Between Four Reaching Targets (Fig. 4) $\omega = 1$. Dark Blue Indicates the Highest Cost, Corresponding to the Farthest Class from the Target Position

Target position class	Predicted Target position class			
	1	2	3	4
1	0	0.15	0.45	0.9
2	0.15	0	0.61	1
3	0.45	0.61	0	0.45
4	0.9	1	0.45	0

Table 6. Confusion Matrix Corresponding to the Worst-Performing Classification in Fig. 4.

Target position class	Predicted Target position class			
	1	2	3	4
1	0	0	0	15
2	0	0	0	15
3	0	15	0	0
4	0	15	0	0

As shown in Table 7, conventional accuracy was identical across the three synthetic confusion matrices (33.3%), despite their different spatial error patterns. Both the proposed modified accuracy and weighted Cohen's kappa distinguished these patterns, assigning the most favorable scores to the near-error pattern and the least favorable scores to the far-error pattern. The two metrics differ, however, in their interpretation and scale.

Table 7. Comparison of conventional accuracy, proposed modified accuracy, and weighted Cohen's kappa for the three synthetic confusion matrices using the spatial cost matrix in Table 5.

Error pattern	Conventional accuracy	Modified accuracy	Weighted Cohen's kappa
Near-error	33.3%	77%	0.5506
Far-error	33.3%	33.3%	−0.1919
Random-error	33.3%	49%	0.0776

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3-5- Validating Distance-Weighted Accuracy on EEG-Based Reaching Target Classification

The proposed distance-weighted accuracy metric was further evaluated using an EEG dataset recorded during a nine-target tabletop reaching task. The dataset was collected from a single participant performing reaching movements toward nine spatially distributed target locations (Fig. 1), with 2-second pre-movement EEG epochs extracted for target classification.

Reaching-target classification was performed using two support vector machine (SVM) classifiers with different kernel functions: a Medium Gaussian kernel SVM (GSVM) and a quadratic kernel SVM (QSVM). The classifiers were implemented in MATLAB R2025a (MathWorks, Natick, MA, USA) and evaluated using 5×2 cross-validation. Differences in performance between the classifiers were assessed using the Combined 5×2 CV F-test. The spatial relationships among the nine target locations were used to construct the misclassification cost matrix (Table 8), which assigns higher costs to errors involving greater spatial distances between the intended and predicted targets. This cost matrix was incorporated into the proposed distance-weighted accuracy metric (Eq. 7).

Both the Quadratic kernel SVM (QSVM, Fig. 5) and the Medium Gaussian kernel SVM (GSVM, Fig. 6) were evaluated using 5×2 cross-validation. The mean conventional classification accuracy was 48.90 ± 6.33% for QSVM and 31.30 ± 8.24% for GSVM, corresponding to a difference of 17.60 percentage points in favor of QSVM. The Combined 5×2 cross-validation F-test indicated that this difference was statistically significant ($F(10, 5) = 13.908$, $p = 0.00476$).

Using the proposed distance-weighted accuracy metric with the primary weighting parameter ($\omega = 1.5$), the mean scores were 87.12 ± 1.75% for QSVM and 75.93 ± 9.44% for GSVM, yielding a difference of 11.19 percentage points. This difference was not statistically significant ($F(10, 5) = 2.2108$, $p = 0.197$).

To further investigate the influence of the weighting parameter (ω), additional analyses were conducted using $\omega = 0.3$ and $\omega = 5$. At $\omega = 0.3$, the mean distance-weighted accuracy was 49.96 ± 6.23% for QSVM and 32.36 ± 8.14% for GSVM, corresponding to a difference of 17.60 percentage points. The Combined 5×2 cross-validation F-test indicated that this difference was statistically significant ($F(10, 5) = 14.396$, $p = 0.00440$). In contrast, at $\omega = 5$, the mean scores were 99.35 ± 0.18% for QSVM and 94.40 ± 10.36% for GSVM, with a difference of 4.95 percentage points. This difference was not statistically significant ($F(10, 5) = 1.0476$, $p = 0.512$).

Overall, QSVM achieved a higher mean distance-weighted accuracy than GSVM across all three weighting parameter settings. However, the difference between classifiers was statistically significant at $\omega = 0.3$ ($p = 0.00440$), but not at $\omega = 1.5$ ($p = 0.197$) or $\omega = 5$ ($p = 0.512$). The mean distance-weighted accuracy increased with larger values of the weighting parameter for both classifiers, reaching 99.35 ± 0.18% for QSVM and 94.40 ± 10.36% for GSVM at $\omega = 5$.

3-6- Discussion

This study adapts and evaluates a spatially weighted accuracy metric for reaching-target classification, in which **misclassification costs are determined according to the Euclidean distance between intended and predicted targets**. Unlike conventional accuracy, which treats all classification errors equally, the proposed **distance-weighted accuracy** accounts for the spatial deviation between predicted and intended targets and therefore distinguishes between spatially close and distant errors. Reporting both conventional

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accuracy and distance-weighted accuracy provides complementary information for evaluating classifier performance in spatially oriented motor-decoding applications.

Consistent with established motor neuroscience findings [6, 7], conventional accuracy can decrease as target proximity increases because adjacent target positions may be more difficult to distinguish. For example, reductions from 96.5% to 77.11% have been reported in [7] due to adjacent-position confusions. Our approach addresses this evaluation gap through two complementary demonstrations.

First, in a synthetic validation setting, engineered confusion matrices with identical conventional accuracy (33.3%) but distinct error patterns (near, far, and random; Tables 2–4) yielded clearly differentiated distance-weighted accuracy values (77%, 33.3%, and 49%, respectively). These results demonstrate the sensitivity of the proposed metric to the spatial distribution of classification errors, which is not captured by conventional accuracy. To further compare the proposed metric with an established cost-sensitive measure, weighted Cohen's kappa was calculated for the three synthetic confusion matrices using the same spatial cost matrix as the proposed modified accuracy, with $\omega = 1$. Both metrics ranked the near-error pattern highest, followed by the random-error pattern and the far-error pattern. However, their scores have different interpretations and are not directly comparable on the same scale. The proposed modified accuracy quantifies performance relative to the task-defined worst-case misclassification cost, whereas weighted Cohen's kappa accounts for expected weighted disagreement under a chance-agreement model. The negative kappa value obtained for the far-error pattern indicates that its observed weighted disagreement exceeded the expected disagreement under this model.

Second, in the EEG-based reaching-target classification experiment, the 5×2 cross-validation analysis yielded mean conventional accuracies of 31.30 ± 8.24% for the Medium Gaussian SVM (GSVM) and 48.90 ± 6.33% for the Quadratic SVM (QSVM), with a mean difference of 17.60 percentage points in favor of QSVM. Using the proposed distance-weighted accuracy metric with the primary weighting parameter ($\omega = 1.5$), the corresponding mean scores were 75.93 ± 9.44% for GSVM and 87.12 ± 1.75% for QSVM, respectively. Although QSVM achieved a numerically higher mean distance-weighted accuracy by 11.19 percentage points, this difference was not statistically significant (Combined 5×2 cross-validation F-test, $F(10, 5) = 2.2108$, $p = 0.197$). Thus, the results do not provide sufficient statistical evidence to conclude that either classifier outperformed the other in terms of distance-weighted accuracy.

Table 8. Misclassification Cost Matrix Between Nine Reaching Targets (Fig. 1) with $\omega = 1.5$, Dark Blue Indicates the Highest Cost, Corresponding to the Farthest Class from the Target Position

True Target position class	Predicted Target position class								
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1	0	0.06	0.24	0.06	0.13	0.33	0.16	0.27	0.54
2	0.06	0	0.11	0.13	0.13	0.26	0.27	0.36	0.63
3	0.24	0.11	0	0.33	0.26	0.28	0.54	0.63	1.00
4	0.06	0.13	0.33	0	0.06	0.24	0.06	0.13	0.33
5	0.13	0.13	0.26	0.06	0	0.11	0.13	0.13	0.26
6	0.33	0.26	0.28	0.24	0.11	0	0.33	0.26	0.28
7	0.16	0.27	0.54	0.06	0.13	0.33	0	0.06	0.24
8	0.27	0.36	0.63	0.13	0.13	0.26	0.06	0	0.11
9	0.54	0.63	1.00	0.33	0.26	0.28	0.24	0.11	0

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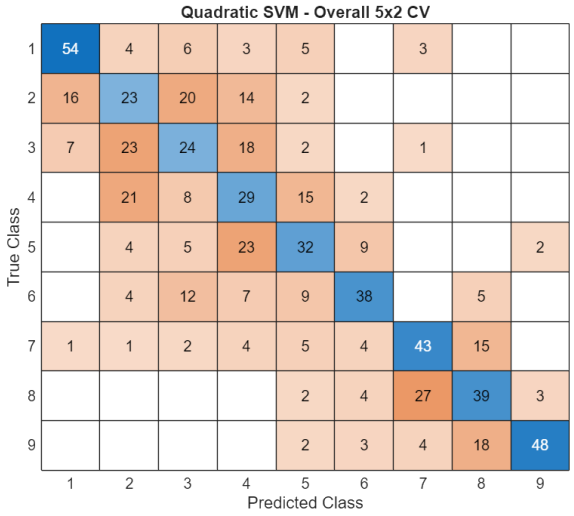


Fig. 5. Overall confusion matrix of the QSVM classifier obtained by pooling target predictions across the ten test evaluations of the 5×2 cross-validation procedure, showing the distribution of correctly and incorrectly classified cases.

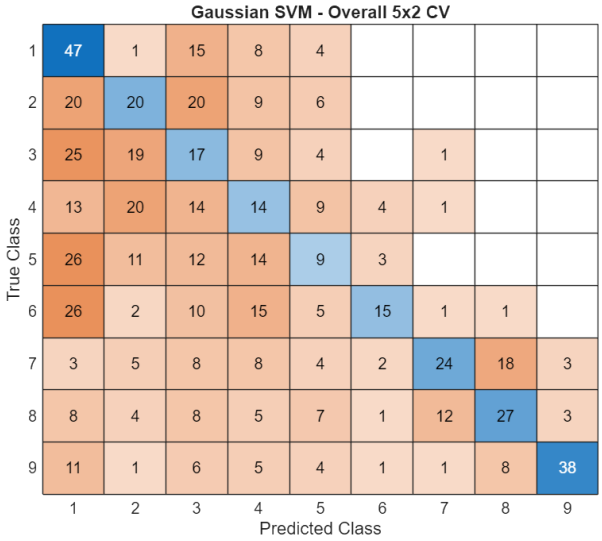


Fig. 6 Overall confusion matrix of the GSVM classifier obtained by pooling target predictions across the ten test evaluations of the 5×2 cross-validation procedure, showing the distribution of correctly and incorrectly classified cases.

Nevertheless, the distance-weighted metric provides complementary information by characterizing the spatial severity of classification errors according to the distance between the predicted and intended targets. The overall confusion matrices obtained from the five repetitions of 2-fold cross-validation further illustrate differences in the classification error patterns of the Quadratic SVM (QSVM) and the Medium Gaussian SVM (GSVM) (Figs. 5 and 6). Although QSVM achieved higher conventional accuracy than GSVM, the confusion matrices reveal that classification errors were distributed differently across target classes. The effect of spatial weighting can be illustrated by examining the predictions for Class 4 in the pooled confusion matrices. For this class, QSVM produced 46 misclassifications, compared with 61 for GSVM,

representing a difference of 15 errors. However, the corresponding spatial misclassification costs were 6.75 for QSVM and 9.56 for GSVM, a difference of 2.81. These results illustrate that spatial misclassification cost depends not only on the number of misclassifications but also on the spatial distances between the intended and predicted targets. The class-specific weighted costs contribute to the total spatial misclassification cost across all target classes, which is normalized by the task-defined worst-case misclassification cost to calculate distance-weighted accuracy. Consequently, when many classification errors occur between spatially nearby targets, their relatively low associated costs can reduce the overall penalty compared with conventional accuracy, which treats all misclassifications equally. This illustrates one mechanism by which distance-weighted accuracy can exceed conventional accuracy and demonstrates how the proposed metric provides a spatially informed assessment of classification performance that complements conventional accuracy.

To further examine the influence of the weighting parameter on these findings, a sensitivity analysis was conducted using $\omega = 0.3$ and $\omega = 5$, in addition to the primary setting of $\omega = 1.5$. The weighting parameter substantially influenced the distance-weighted accuracy scores of both QSVM and GSVM. At $\omega = 0.3$, the difference between the classifiers was statistically significant ($F(10, 5) = 14.396$, $p = 0.00440$), whereas at $\omega = 1.5$ ($F(10, 5) = 2.2108$, $p = 0.197$) and $\omega = 5$ ($F(10, 5) = 1.0476$, $p = 0.512$), it was not. Notably, the difference in mean distance-weighted accuracy decreased from 17.60 percentage points at $\omega = 0.3$ to 11.19 percentage points at $\omega = 1.5$ and 4.95 percentage points at $\omega = 5$. This pattern indicates that the choice of weighting parameter affects both the numerical magnitude of the scores and the statistical outcome of the classifier comparison by modifying the relative costs assigned to misclassifications at different spatial distances. The higher distance-weighted accuracy values compared with conventional accuracy should not be interpreted as higher percentages of correctly classified targets. Instead, they reflect the reduced penalties assigned to errors involving spatially nearby targets and therefore provide complementary information about the spatial severity of classification errors. These findings highlight the importance of reporting and justifying the weighting parameter according to the spatial characteristics and requirements of the task. Further research is needed to investigate parameter selection across different target configurations and determine whether movement-phase-dependent weighting could provide additional value in dynamic reaching tasks.

Beyond its implications for classifier evaluation, the ability to distinguish between spatially different classification errors may be particularly relevant to reaching and rehabilitation applications, where the consequences of misclassification depend on the distance between the intended and predicted targets. Errors requiring larger corrective movements may increase movement time and physical effort, while spatially inappropriate predictions may affect task execution in assistive robotic systems. The proposed metric may therefore provide useful supplementary information when evaluating classifiers for these applications.

An important limitation of the present study is the use of data from a single participant and a single target configuration. Consequently, inter-subject variability could not be assessed, and the generalizability of the reported classification results to a broader population remains uncertain. In addition, the proposed distance-weighted accuracy framework was evaluated within a specific EEG-based reaching-target classification task and target configuration. The findings should therefore be interpreted as an initial evaluation of the framework rather than comprehensive evidence of its generalizability across participants, target layouts, or classification settings. Regarding parameter sensitivity, three weighting parameter values were investigated in the EEG-based classification experiment, in addition to one parameter setting used for the synthetic confusion-matrix demonstration. Thus, four parameter settings were considered across the two validation

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stages. Further analysis is needed to characterize the sensitivity of the proposed metric to parameter selection under different task requirements.

Future studies should validate the framework using larger and more diverse participant populations, alternative target configurations, and additional classification settings. Its applicability to other sensing modalities, such as electromyography (EMG) and inertial measurement units (IMUs), could also be investigated to assess its utility across different motor-decoding paradigms. Further research could explore alternative spatial cost functions and investigate the integration of spatially informed evaluation into real-time reaching systems. In particular, movement-phase-dependent weighting could be examined to determine whether adjusting misclassification costs according to the stage of movement or the remaining time to target acquisition provides additional benefits in dynamic reaching tasks. Such extensions would require separate empirical validation before their practical utility could be established. Overall, distance-weighted accuracy may offer complementary information to conventional accuracy and chance-corrected measures by explicitly representing the spatial consequences of classification errors, with potential relevance to motor-decoding and rehabilitation-oriented applications.

4. Conclusion

This study demonstrates that a **distance-weighted accuracy metric based on misclassification costs derived from normalized inter-target Euclidean distances** can provide information about the spatial severity of classification errors that is not captured by conventional accuracy. While conventional accuracy yielded identical performance for the three synthetic confusion matrices (33.3%), the proposed metric produced distinct scores for different spatial error patterns (77%, 33.3%, and 49%), demonstrating its sensitivity to the spatial distribution of misclassifications. In the EEG-based reaching-target classification task, the 5×2 cross-validation analysis yielded mean conventional accuracies of 48.90 ± 6.33% for the Quadratic SVM (QSVM) and 31.30 ± 8.24% for the Medium Gaussian SVM (GSVM), a difference of 17.60 percentage points in favor of QSVM. The statistical comparison using the Combined 5×2 cross-validation F-test indicated a significant difference in conventional accuracy between the classifiers ($F(10, 5) = 13.908$, $p = 0.00476$), favoring QSVM. Using the proposed distance-weighted accuracy metric with the primary weighting parameter $\omega = 1.5$, the mean scores were 87.12 ± 1.75% for QSVM and 75.93 ± 9.44% for GSVM, a difference of 11.19 percentage points. However, the corresponding Combined 5×2 cross-validation F-test did not indicate a statistically significant difference in distance-weighted accuracy ($F(10, 5) = 2.2108$, $p = 0.197$). Thus, QSVM significantly outperformed GSVM in conventional accuracy, whereas the observed advantage in distance-weighted accuracy was numerical but did not reach statistical significance at the $\alpha = 0.05$ level. This result does not establish that the classifiers are equivalent; rather, the analysis did not provide sufficient evidence to conclude that their distance-weighted accuracies differed statistically. These findings indicate that distance-weighted accuracy provides complementary information by characterizing the spatial severity of classification errors according to the distance between the predicted and intended targets.

The additional analysis further demonstrated that the selected weighting parameter (ω) substantially affects the magnitude of distance-weighted accuracy. Therefore, the value of ω should be explicitly reported and justified, and changes in distance-weighted accuracy associated with different ω values should not be interpreted directly as changes in classifier performance. An important limitation of the present study is the use of data from a single participant and a single target configuration. Future work should evaluate the proposed framework using larger and more diverse participant populations, different target layouts, and

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different motor-decoding settings. Future studies should also investigate alternative cost functions and the potential use of movement-phase-dependent weighting to determine whether the framework can be adapted to dynamic reaching tasks. While further validation is warranted, the proposed framework provides a **spatially informed approach for evaluating reaching-target classification** and may offer complementary information for motor-decoding and rehabilitation-oriented applications.

List of Symbols

English symbols

C	Misclassification cost
C_{ij}	Cost of misclassifying true class *i* as predicted class *j*
$C_{i\max}$	Maximum misclassification cost for true class *i* (farthest target)
d_{ab}	Euclidean distance between target positions *a* and *b*, cm
$d_{\max}$	Maximum inter-target Euclidean distance, cm
L_k	Total misclassification cost for classifier *k*
L_{wc}	Worst-case misclassification cost
n_{ij}	Number of trials of true class *i* classified as class *j*
n_i	Total number of trials belonging to true class *i*
N	Number of target classes
x_a, y_a, z_a	Cartesian coordinates of target *a*, cm
x_b, y_b, z_b	Cartesian coordinates of target *b*, cm

Greek symbols

δ_{ab}	Normalized Euclidean distance between targets *a* and *b*
λ	Parameter of the normalized rational cost function
ω	Parameter of the saturating power cost function

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