Prototype Reduction on sEMG Data for Instance-based Gesture Learning towards Real-time Prosthetic Control

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Abstract: Current systems of electromyographic prostheses are controlled by machine learning techniques for gesture detection. Instance-based learning showed promising results concerning classification accuracy and robustness without explicit model training. However, it suffers from high computational demands in the prediction phase, which can be problematic in real-time scenarios. This paper aims at combining such learning schemes with the concept of prototype reduction to decrease the amount of data processed in each prediction step. First, a suitability assessment of state-of-research reduction algorithms is conducted. This is followed by a practical feasibility analysis of the approach. For this purpose, several datasets of signal classes from exerting specific gestures are captured with an eight-channel EMG armband. Based on the recorded data, prototype reduction algorithms are comparatively applied. The dataset reduction is characterized by the time needed for reduction as well as the possible data reduction rate. The classification accuracy when using the reduced set in cross-validation is analyzed with an exemplary kNN classifier. While showing promising values in reduction time as well as excellent classification accuracy, a reduction rate of over 99% can be achieved in all tested gesture configurations. The reduction algorithms LVQ3 and DSM turn out to be particularly convenient.

1 MOTIVATION AND RELATED WORK

The k nearest neighbour classification technique (kNN) as an exemplary instance-based machine learning scheme has shown several advantageous properties in the context of gesture recognition (intent detection) based on surface electromyography (sEMG) signals for prosthetics. In preliminary studies, kNN showed promising results in classification accuracy, generalizability, as well as user study success rate (Cipriani et al., 2011; Geethanjali, 2015; Tello et al., 2013; Khushaba et al., 2016; Sziburis et al., 2020). Moreover, it turned out to perform well in terms of robustness, i. a., against sampling frequency variation (Chen et al., 2017) and electrode shift (Li et al., 2016). It is characterized by a comparably low implementation complexity. Furthermore, instance-based learning schemes provide the benefits of no explicit mathematical model generation, and incrementality, i. e. the possibility to extend the dataset by new samples at any time with them being equally considered.

While these characteristics speak in favour of embedded applicability in the context of wearable real-time systems, an important drawback of instance-based learning schemes is the necessity of comparing new arriving data instances (samples) in the prediction phase to all already stored ones. The needed iterations over all samples lead to potentially computationally intense operations, depending on the amount of data, i. e. the samples to be iterated in every prediction step (Sziburis et al., 2020).

For this reason, this work analyzes the suitability of concepts to reduce the computational effort during prediction in instance-based learning schemes. Although no explicit model training takes place, the data stored in memory is referred to as *training data* in this paper.

Two main approaches to improve the performance in this regard can be pointed out. The first possibility

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is the utilization of memory-efficient, optimized data structures, e. g. "ball-tree data structures, hashing" (Kusner et al., 2014).

The second approach is data reduction and aims at decreasing the amount of signal data gathered during training and stored in memory. It can be principally applied in a horizontal (feature space) and in a vertical dimension (sample space). Aside from that, there are techniques using approximations, such as Large Margin Nearest Neighbour (Kusner et al., 2014) for kNN.

Horizontal data reduction is limited by the high variance of EMG signals. Nevertheless, the concept of feature selection (or horizontal thinning) has been applied in the context of pattern-recognition-based prosthetic control for datasets of high feature space dimensions, e. g. in the form of biologically inspired methods such as genetic algorithms and particle swarm optimization (Purushothaman, 2016). Further concepts of horizontal data reduction are feature discretization, projection and positioning (Kusner et al., 2014). These come along with dimensionality reduction algorithms, e. g. PCA (Güler and Koçer, 2005) and adaptions (Nagata et al., 2005) as well as variants of LDA (Negi et al., 2016).

The concept of vertical data reduction is mainly referred to as *prototype reduction*. This paper will examine techniques of this group in the context of EMG gesture data. *Prototype* stands for data instance or sample. However, it also indicates that it refers to specific instances that represent a larger amount of instances to a certain extent.

García et al. (García et al., 2012) and Triguero et al. (Triguero et al., 2012) provide an overview of a variety of prototype reduction algorithms proposed. The methods are divided into two groups: On the one hand prototype selection (selecting a subset of instances from the existing ones stored in memory, also called vertical thinning), and on the other hand prototype generation (creating new instances based on the existing ones to represent the whole dataset).

2 CONCEPTUAL APPROACH

The presented approach consists of reducing the computational effort of prediction steps by decreasing the number of samples within the gesture dataset. For this purpose, the term *reduction rate* describes the number of samples finally stored in memory relative to the number of originally recorded samples.

2.1 Theoretical Requirements

First, an assessment of the variety of algorithms reviewed in (García et al., 2012) for prototype selection and (Triguero et al., 2012) for prototype generation will be conducted, regarding the suitability of each method. Suitable methods should not influence the incrementality of the applied instance-based classifier and provide a possibility to specify the number of prototypes in the final set or accordingly the reduction rate beforehand. The latter characteristic will be called *size determinism* in the following.

Moreover, there is the requirement of real-time capability which refers to the prediction phase of gesture recognition, since this phase takes place online and continuously decides on user satisfaction. The real-time property is guided by timing determinism, i. e. executing an identical number of operations per prediction. This can be achieved by establishing the same number of stored instances to be considered in each prediction step. To guarantee that, size determinism is inherently necessary. In order to provide fast reaction times, the number of stored samples should be as low as possible. Additionally, by providing size determinism, deterministic memory demands are facilitated.

In the training phase, in contrast, sample capturing and offline calculations take place, which are not meant to be applied in real-time. Therefore, it is not particularly needed to cope with real-time requirements in this phase. However, training computations should progress as fast as possible to avoid delays for the user between training and utilizing the gesture prediction system.

2.2 Practical Methods

After their theoretical assessment, promising algorithms will be practically evaluated in experiments on datasets of the linear envelope of rectified EMG signals. They consist of samples captured when exerting multiple sets of varying gesture configurations with an eight-channel state-of-the-art armband positioned on the forearm. With that, one sample is composed of eight 32-bit floating-point values.

Within one dataset, four repetition blocks are alternatingly recorded for each of the gestures, whereat each repetition block consists of 400 samples (i. e. two seconds offline data sample recording at a capturing rate of 200 Hz) per gesture. Overall, three such datasets with slightly differing sensor positionings are recorded per gesture configuration.

The following differing gesture configurations are selected in order to test the reduction algorithms' potential dependence on inter-class properties:

- rest state, power grasp, wrist flexion, wrist extension (6400 samples per dataset),
- rest state, power grasp, pointing, wrist flexion, wrist extension (8000 samples per dataset),
- rest state, power grasp, wrist flexion, wrist extension, wrist pronation, wrist supination (9600 samples per dataset), and
- rest state, power grasp, pointing, wrist flexion, wrist extension, wrist pronation, wrist supination (11200 samples per dataset).

The mentioned inter-class property dependence could occur in the case of by-trend overlapping classes, as in power grasp and pointing gesture where similar groups of muscles are addressed for gesture exertion (apart from the index finger degree of freedom specifically needed for the pointing gesture). Another potential case could be wrist flexion and supination, as well as wrist extension and pronation, which respectively address the same groups of muscles, again with the exception of individual single degrees of freedom. Another reason for selecting several gesture configuration sets is the aim to analyze the dependence of dataset reduction on the initial dataset size due to differing sample numbers.

The achieved accuracies using the reduced sets will be assessed in cross-validation with an exemplary kNN classifier. Since the assumption of independent and identically distributed random variables does not hold for samples within the same repetition block of one gesture due to the time-dependent capturing process, a group-wise cross-validation scheme is applied. This means that prototype reduction takes place on the combined set of one repetition block per gesture (group) and the resulting prototype samples are only validated against samples from other groups, i. e. not against those from the same group. The average will be taken for all possible groupings per algorithm and gesture configuration (folds).

The kNN configuration is chosen to apply a weighting of the distance d by $1/d^2$ with a Euclidean distance metric. With selecting $k = 1$, the algorithmic runtime behaviour of the validation classifier can be reduced from $O(n \cdot \log(n))$ (due to sorting) to $O(n)$ (minimum search) with n being the number of samples in the reduced set. This was chosen as classifier setting.

Besides accuracy, the averaged runtime will be analyzed. The runtime consists of two components, namely the reduction time of the algorithm plus the time needed for validation. Since the validation is the same process for each cross-validation fold within datasets of the same gesture configuration, the validation time can be disregarded for the purpose of comparison. Considering that, the runtime constitutes a representative measure for the algorithms' reduction times.

3 THEORETICAL ASSESSMENT

Among the prototype selection algorithms in (García et al., 2012) only Random Mutation Hill Climbing RMHC (Skalak, 1994) inherently possesses the characteristic of size determinism, as it is the only method with *fixed* reduction. However, RMHC is a wrapper method, which means that in each step the decision if to select a prototype or not, a complete classifier evaluation has to take place so that high computation times during the reduction process have to be expected. In (García et al., 2012, p. 425–427) it is shown that this assumption holds in real use-cases for variably sized sets of data. Exemplary tests on EMG datasets confirmed this behaviour so that RMHC was excluded from further consideration.

Besides the fixed reduction prototype selection algorithms, there may be also *mixed* reduction methods which provide the property of determinism with respect to the number of samples contained in the final training set. Nevertheless, the algorithms of that category described in (García et al., 2012) are all wrapper methods, too. Due to the respective high execution times as mentioned before, these methods are not considered within the scope of this work.

In terms of prototype generation, there is a variety of *fixed* reduction approaches, structured as follows:

- *Positioning Adjustment, Condensation:* Vector Quantization VQ (Qiaobing Xie et al., 1993), Learning Vector Quantization (LVQ) methods: LVQ3 (Kohonen, 1990), LVQ with Training Counter LVQTC (Odorico, 1997), Decision Surface Mapping DSM (Geva and Sitte, 1991),
- *Positioning Adjustment, Hybrid Approach:* Particle Swarm Optimization PSO (Nanni and Lumini, 2009),
- *Centroid-based Condensation:* Bootstrap Techniques BTS3 (Hamamoto et al., 1997), Adaptive Condensing Algorithm Based on Mixtures of Gaussians MGauss (Lozano et al., 2006),
- *Space-splitting:* Chen Algorithm (Chen and Jóźwik, 1996).

LVQTC does not provide size determinism so that it was not taken into account for further evaluation, while the other algorithms will be practically examined.

Besides the *fixed* algorithms, also in prototype generation there are *mixed* methods again, which may principally also provide size determinism:

- *Positioning Adjustment, Condensation:* Gradient Descent and Deterministic Annealing MSE (Decaestecker, 1997), Hybrid LVQ3 HYB, (Kim and Oommen, 2003), LVQ with Pruning LVQPRU (Li et al., 2005),
- *Positioning Adjustment, Hybrid Approach:* Prototype Selection Clonal Selection Algorithm PSCSA (Garain, 2008) using an artificial immune system model, Evolutionary Nearest Prototype Classifier ENPC (Fernández and Isasi, 2004), Adaptive Michigan PSO AMPSO (Cervantes et al., 2007),
- *Centroid-based Hybrid Approach:* Integrated Concept Prototype Learner ICPL2 (Lam et al., 2002).

In turn, some of these are wrapper methods (ENPC, AMPSO) and hence not considered with regard to the previously mentioned reason. The filter and semi-wrapper methods MSE, HYB, and ICPL2 do not provide size determinism.

Overall, the remaining methods to practically analyze in the subsequent section are MGauss, BTS3, Chen, LVQ3, LVQPRU, DSM, VQ, and PSCSA.

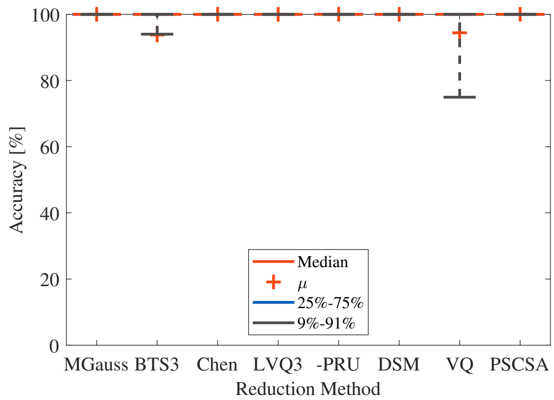
4 PRACTICAL EVALUATION

Following the experimental configuration presented in section 2.2, exemplary experiments showed that a reduction to 20 prototypes in the final set yields a promising performance (regarding reduction time and classification accuracy), which was hence set as the goal.

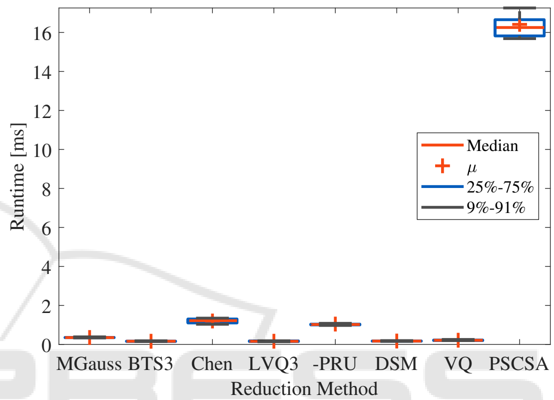
Figures 1 to 4 illustrate the results of cross-validation accuracies and runtimes per algorithm and gesture configuration, averaged over all validation folds for the corresponding datasets.

The time measurements refer to the usage of the open-source (GPLv3) tool KEEL (*Knowledge Extraction based on Evolutionary Learning*) (Triguero et al., 2017) on GNU/Linux kernel 4.18.0-25 (Intel Core i7-8550U, 1.80 GHz, 7869 MiB RAM) with only essential system processes running.

Each repetition block is supposed to have the same size, just slightly differing due to sampling rate deviations when the training data was captured. The training data is reduced to 20 samples (i. e. 20 times eight channel values with a 32-bit floating-point number per channel) in each procedure.



(a) Accuracy

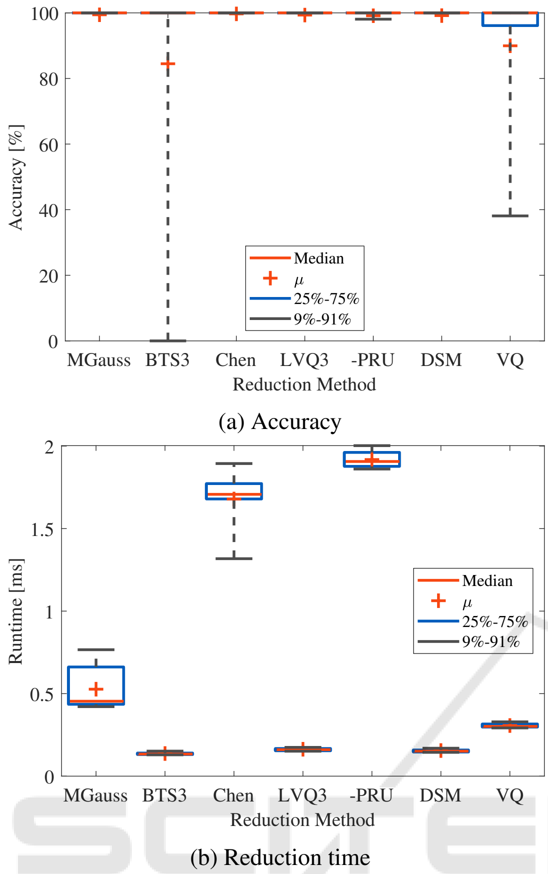


(b) Reduction time

Figure 1: Averaged performance results for datasets with four gestures (rest, power, flexion, extension).

Figure 1 shows equally high classification accuracies (100%) for all algorithms in all cases, with small exceptions for BTS3 and VQ exposing some outliers and therefore higher variance. However, even these methods yield 100% as median and over 90% as mean. In terms of time, PSCSA is noticeably worse than the other algorithms which all deliver times under 2 ms vs. 17 ms for PSCSA. Due to this high discrepancy already in a case with only four gestures and better performance of the other methods in all cases, PSCSA was excluded from further consideration.

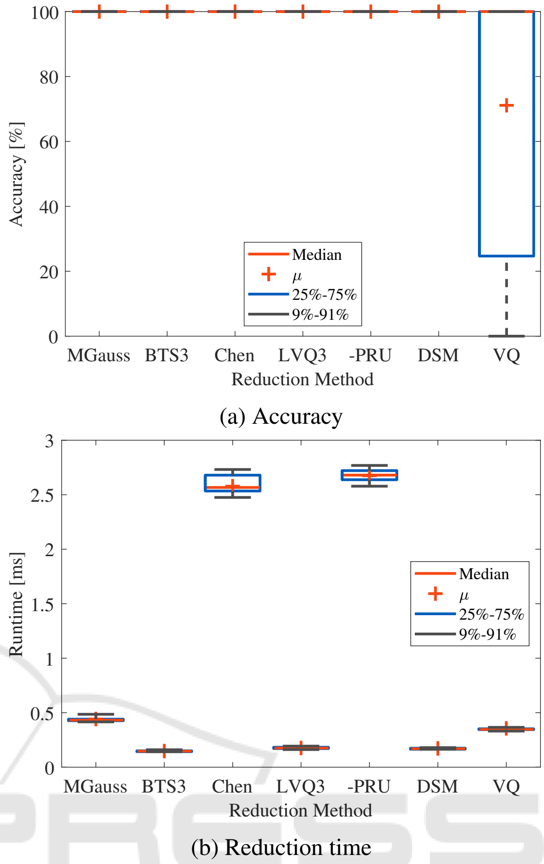
When additionally including the pointing gesture (figure 2), i. e. introducing a by-trend overlapping class, differences among the algorithms can be observed. BTS3 and VQ again show high variances in accuracy. In comparison to the previous dataset, they perform even worse, reducing the accuracies from slightly over 90% in mean to about 85% and 90% respectively. The other algorithms' accuracy means are still close to or at 100%. All medians still lay at 100%. Chen, MGauss and LVQPRU have a comparably broad variance of runtime, leading to the assump-



(a) Accuracy

(b) Reduction time

Figure 2: Averaged performance results for datasets with five gestures (rest, power, point, flexion, extension).



(a) Accuracy

(b) Reduction time

Figure 3: Averaged performance results for datasets with six gestures (rest, power, flexion, extension, pronation, supination).

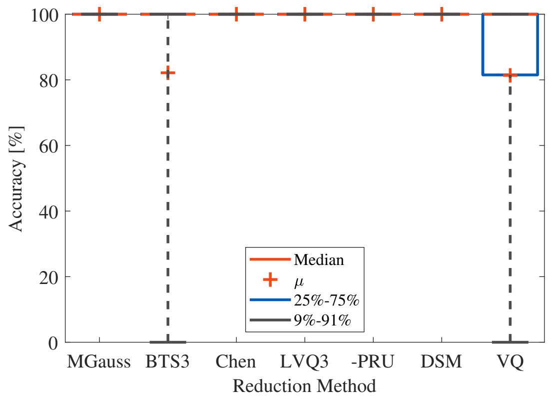
tion of higher nondeterminism during execution. Furthermore, these three algorithms yielded the highest means and medians in runtime.

A dataset without point gesture but with wrist pronation and wrist supination (figure 3) does not seem to affect the accuracy of BTS3 anymore (constantly at 100%), although VQ's results even more (accuracy mean of 70% but still median of 100%). The other schemes provide 100% in all cases. The timings of Chen and LVQPRU still show the highest mean and median as well as variance. Among the remaining algorithms, MGauss and VQ are slightly slower than BTS3, LVQ3, and DSM.

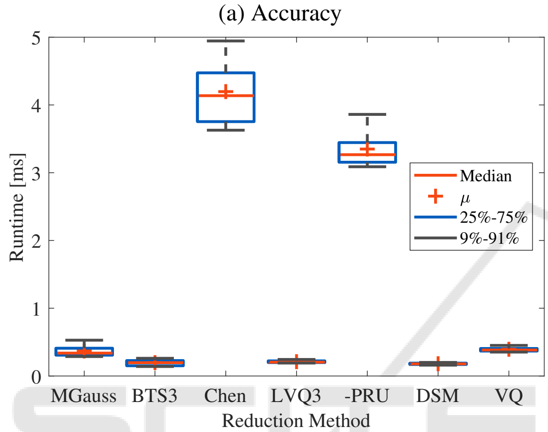
Testing all gestures, i. e. including pointing gesture as well as wrist rotations (figure 4), summarizes previous observations, i. e. the reduced accuracy of BTS3 and VQ with a mean of about 80% while the others provide 100%. All algorithms expose a median accuracy of 100%. Regarding timing, Chen and LVQPRU have the highest means and medians. Furthermore, their timing variance can be considered as high, leading to the presumption of reduced time determinism.

5 DISCUSSION AND OUTLOOK

The results showed that the approach of prototype reduction seems promising to cope with the main drawback of instance-based learning in the context of EMG-based gesture detection for real-time embedded applications, such as prosthetic control. The examined algorithms are suitable to be used with any instance-based learning technique; the general feasibility could be demonstrated with a kNN classification scheme. The reduction of data processed in prediction to a deterministic and low number of 20 data samples (i. e. reduction rate of over 99%) while preserving excellent classification accuracy could be successfully shown. With that, data with no informational content regarding classification can be disregarded. The very high possible reduction rate points out the prevalent existence of that kind of data. However, detailed analyses of the dependence on reduction rate have to be conducted, considering a higher number and greater variety of gesture datasets as well as



(a) Accuracy



(b) Reduction time

Figure 4: Averaged performance results for datasets with seven gestures (rest, power, point, flexion, extension, pronation, supination).

the influence of the chosen classifier and its parameterization.

While the main aspect of coping with computationally high demands in real-time instance-based learning is the prediction phase, the training phase has no explicit real-time requirement as it takes place in an offline manner. However, the training time should be as short as possible in order to avoid delays for the user before being able to interact with the system, which is especially important in actual wearable prosthetic devices. On the present simulation system, prompt training runtimes under 0.5 ms could be achieved in all datasets for the best-performing algorithms (including cross-validation time). The timing characteristics have to be further evaluated on differing types of embedded systems, under consideration of specific requirements in prosthetic applications.

For all used combinations of gestures, especially LVQ3 and DSM (both based on Learning Vector Quantization, LVQ) turned out to be of particular interest. The PSCSA algorithm was already disregarded in an early stage due to around 16 times higher run-times in comparison to the other methods, which can be related to the complexity of the artificial immune system model behind.

While all evaluated algorithms interestingly yielded 100% as median after reducing the original datasets to 20 samples, LVQ3, DSM, Chen and MGauss provided 100% classification accuracy even as mean value. Among these methods, MGauss and especially Chen exhibit comparably high reduction times (together with LVQPRU).

With a low runtime of about 0.2 ms in most cases and a low runtime variance, LVQ3 and DSM seem to be the most suitable among the tested reduction algorithms for real-time scenarios and embedded applications. This will be subject to further research, with specifically adapting the algorithmic programming and hardware frameworks as well as an in-depth examination of time complexity and tuning all parameters involved. Moreover, user studies have to be conducted with participants performing target achievement tests in online gesture classification and real-time prosthetic control applications.

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