

Deep learning with convolutional neural networks: a resource for the control of robotic prosthetic hands via electromyography

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Deep learning with convolutional neural networks applied to electromyography data: a resource for the classification of movements for prosthetic hands.

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7 **Keywords: electromyography₁, prosthetics₂, rehabilitation robotics₃, machine learning₄, deep
8 learnings₅, convolutional neural networks₆**

9 **Abstract (350 words)**

10 Natural control methods based on surface electromyography and pattern recognition are promising
11 for hand prosthetics. However, the control robustness offered by scientific research is still not
12 sufficient for many real life applications and commercial prostheses are capable of offering natural
13 control for only a few movements.

14 In recent years deep learning revolutionized several fields of machine learning, including computer
15 vision and speech recognition. Our objective is to test its methods for natural control of robotic hands
16 via surface electromyography using a large number of intact subjects and amputees.

17 We tested convolutional networks for the classification of an average of 50 hand movements in 67
18 intact subjects and 11 transradial amputees. The simple architecture of the neural network allowed
19 to make several tests in order to evaluate the effect of pre-processing, layer architecture, data
20 augmentation and optimization. The classification results are compared with a set of classical
21 classification methods applied on the same datasets.

22 The classification accuracy obtained with convolutional neural networks using the proposed
23 architecture is higher than the average results obtained with the classical classification methods but
24 lower than the results obtained with the best reference methods in our tests.

25 The results show that convolutional neural networks with a very simple architecture can produce
26 accuracy comparable to the average classical classification methods. They show that several factors
27 (including pre-processing, the architecture of the net and the optimization parameters) can be
28 fundamental for the analysis of surface electromyography data. Larger networks can achieve higher
29 accuracy on computer vision and object recognition tasks. This fact suggests that it may be
30 interesting to evaluate if larger networks can increase sEMG classification accuracy too.

31

32 1 Introduction

33 Transradial amputees can be highly impaired, even if equipped with the most modern prostheses. The
34 recent advances in deep learning and convolutional neural networks may contribute to help them
35 recovering some of their capabilities by bridging the gap between the prosthetics market (that
36 requires fast and robust control methods) and recent scientific research results in rehabilitation
37 robotics (that shows that dexterous and proportional control is possible).

38 Currently, the prosthetics market offers myoelectric prosthetic hands that are extremely advanced
39 from a mechanical point of view and that can perform many different movements. However, the
40 control methods are still in most cases rudimentary in order to guarantee 100% control robustness
41 and sufficient control speed. Many myoelectric prosthetic hands are commercially available,
42 however, few of them have the capability to reproduce many different movements. A selection of the
43 most advanced prosthetic hands available in the market according to their movement capabilities
44 currently include the following ones: 1) Vincent hand Evolution 2; 2) Steeper Bebionic v3; 3) Otto
45 Bock Michelangelo; 4) Touch Bionics i-limb Quantum (Atzori and Müller, 2015). Some of these
46 prostheses are characterized by very high dexterity: they allow the movement of up to 5 different
47 fingers independently. They allow the rotation of the thumb, to reproduce up to 36 different
48 movements and the rotation of the wrist in near real time. In general, a commercial myoelectric
49 prosthesis is opened or closed through the contraction of specific remnant muscles. While the
50 mechanical characteristics of the mentioned prostheses are advanced, the control systems rely in most
51 cases on specific movement triggers or sequential control strategies. Movement triggers link specific
52 surface electromyography (sEMG) pulse sequences to specific movement of the prosthesis.
53 Sequential control strategies allow to shift between a set of predefined movements through specific
54 signals (e.g. through co-contraction, i.e. the simultaneous activation of two sEMG electrodes). Some
55 of the considered prostheses include external sources of information in the form of active falling
56 object prevention systems or via smartphones. Touch Bionics offers a selection of grasps according
57 to objects located near the prosthesis (using Near-Field Communication, NFC) or according to action
58 patterns (using accelerometer and gyroscope measurements). In the most advanced cases, pattern
59 recognition is also used to control the prosthesis in combination with traditional methods. This
60 solution has been proposed since 2013 by Coaptengineering and it was recently introduced by Touch
61 Bionics to control wrist rotation. The mentioned control methods offer robust results, which are
62 deemed to be one of the main needs in real use (Farina et al., 2014a). However, the movement
63 imagined to control the prosthesis is not natural, since it does not correspond to the movement that
64 the amputee would have imagined to do in order control his real hand before the amputation. It also
65 does not allow to control a large set of movements.

66 Proportional, natural and dexterous controls of robotic hand prostheses have been studied for a long
67 time by scientific researchers. However, current results are still not robust enough to be translated to
68 real life use. Most of the methods rely on the use of sEMG and pattern recognition or proportional
69 control algorithms. Pattern recognition algorithms are used to classify the movement that the subject
70 aims to perform according to a label (Scheme and Englehart, 2011). The classification accuracy can
71 be higher than 90%-95% on less than 10 classes. However, average results are usually below 80-90%
72 (Peerdeman et al., 2011a). Simultaneous pattern recognition has been studied recently (Jiang et al.,
73 2013; Ortiz-Catalan et al., 2013; Young et al., 2013). Proportional and simultaneous control of a
74 large number of degrees of freedom of the prosthesis can allow achieving more natural and dexterous
75 control using unsupervised or supervised methods (Farina et al., 2014b; Fougner et al., 2012).
76 Recently, semi-supervised methods and supervised methods were compared to evaluate the impact of
77 precise kinematic estimations for accurately completing goal-directed tasks (Jiang et al., 2014).

78 Real time studies allowing the user to adapt his response to the control software can provide a good
79 representation of prosthesis usability (Hargrove et al., 2007; Scheme and Englehart, 2011). However,
80 since these studies require the interaction of the user with the control system, they do not allow easy
81 comparison with innovative analysis procedures. Another common problem in the field is that the
82 studies are often highly specific and they are not directly comparable due to different acquisition
83 setups, protocols and analysis pipelines. Moreover, often the datasets are not publicly available. The
84 usefulness of benchmark databases has been demonstrated repeatedly in other fields, e.g., in the
85 machine vision and image analysis communities (Everingham et al., 2010; Müller et al., 2009).
86 Offline data analysis on public benchmark datasets allows the comparison of different methods and
87 setups, accelerating the search and pushing forward progress in prosthetic control robustness. In 2014
88 the biggest publicly available benchmark database was released by the NinaPro project (Atzori et al.,
89 2015). It consists of 3 datasets containing sEMG, accelerometer, and both hand kinematic and
90 dynamic data recorded from 67 intact subjects and 11 amputees performing at least 50 hand
91 movements.

92
93 Promising results have been obtained with invasive methods such as Peripheral Nerve Interface
94 (Urbanek et al., 2012), Cortical Interface (Chestek et al., 2011) or Targeted Muscle Reinnervation
95 (TMR) (Kuiken et al., 2009). The latter has shown very promising results, especially in transomeral
96 or shoulder amputees (Atzori and Müller, 2015). TMR consists of the re-innervation of spare muscles
97 of the amputee with the residual nerves of the amputated limb. However, the invasiveness of the
98 procedure can strongly limit the application possibilities. A recent survey explored the interest of
99 upper-limb amputees in four different techniques for prosthetic control: myoelectric, TMR,
100 peripheral nerve interfaces, and cortical interfaces. Participants expressed the most interest in the
101 myoelectric control, while the cortical interface elicited the lowest interest (Engdahl et al., 2015).
102 This highlights that invasive techniques can be rejected by amputees.

103
104 Multimodal data acquisition has also been investigated. Computer vision has been combined with
105 sEMG-based detection of movement intention to predetermine the type and size of the required grasp
106 in relation to the object (Došen et al., 2010; Markovic et al., 2014). Accelerometers showed excellent
107 capabilities to recognize hand movements using pattern recognition and regression methods, both
108 alone and in combination with sEMG electrodes (Atzori et al., 2014c; Gijssberts et al., 2014;
109 Krasoulis et al., 2015).

110
111 Nevertheless, despite several improvements on the market and scientific research, the robust natural
112 control of dexterous prosthetic hand is still missing.

113
114 Deep learning and convolutional neural networks recently revolutionized several fields of machine
115 learning, including speech recognition and computer vision. Thus, it seems reasonable to investigate
its abilities in surface electromyography as well.

116
117 Despite it often being considered a new and emerging field, the birth of deep learning can be set in
118 the 1940s. It passed through several stages and names over the years: born and known as *cybernetics*,
119 it became popular as *connectionism* between the 1980s and 1990s, while since 2006 it started to be
120 called with the current name (Goodfellow et al., 2016). In Goodfellow et al., the increasing dataset
121 and model sizes are recognized as key points of the new success of this kind or approach
122 (Goodfellow et al., 2016). Thanks to the hardware and software advances it is now possible to use
large networks trained with large datasets, allowing the exploitation of their capabilities.

123 Deep neural networks have been successful in several applications since the 1980s. However, in the
124 field of computer vision in 2012, their use won one of the largest object recognition challenges (the
125 ILSVRC) decreasing the previous top-5 error rate by more than 10% (Goodfellow et al., 2016;
126 Krizhevsky and Hinton). Since then, only techniques based on convolutional neural networks have
127 won this competition, leading to top-5 error rates lower than 5% (Goodfellow et al., 2016; He et al.,
128 2015). Another remarkable result in computer vision was obtained in 2012, when human-level results
129 were reached using multi-column deep neural networks on computer vision benchmarks (Cireşan et
130 al., 2012). In the computer vision field, deep neural networks are also successfully applied in
131 pedestrian detection (Sermanet et al., 2013) and traffic sign classification (Cireşan et al., 2012).

132 Since 2010 the application of deep learning techniques to speech recognition has allowed a quick and
133 impressive reduction of error rate (Dahl et al., 2010; Deng et al., 2010b, 2013; Goodfellow et al.,
134 2016; Hinton et al., 2012)

135 Deep learning methods are also successfully applied to applications requiring the process of big
136 amount of data, such as drug discovery (Ramsundar et al., 2015), compound activities prediction
137 (Dahl et al., 2014), and genomic information annotation (Chicco et al., 2014). Moreover, they have
138 also improved the performance of reinforcement learning, where a machine or software agent is able
139 to maximize its performance by itself performing trials and errors (Goodfellow et al., 2016; Mnih et
140 al., 2015).

141 As reported, the deep neural network applications are several and continuously increasing. However,
142 convolutional neural networks have been applied to sEMG hand movement recognition mainly in a
143 single conference paper. Park and Lee (Park and Lee, 2016) used a convolutional neural network
144 model composed of an input layer, four convolutional layers, four subsampling layers, and two fully
145 connected layers to improve inter-user variability in six hand movements via sEMG signals. The
146 strategy adopted was to perform a first non-adaptation experiment, applying a trained model (or
147 classifier) and a second experiment using a retrained model (or classifier) using few labeled data. The
148 results show a better classification accuracy for the convolutional neural network compared to
149 Support Vector Machines (SVM) in both experiments. The highest accuracy was reached using
150 convolutional neural networks with the retrained network.

151 In this paper we apply convolutional neural networks to the classification of 50 hand movements in
152 67 intact subjects and 11 hand transradial amputees and we compare the results with those obtained
153 with classical machine learning methods on three Ninapro datasets (Atzori et al., 2014b). The
154 Ninapro database is particularly useful for this analysis since it provides publicly available data and
155 reference classification performances with classical machine learning procedures.

156

157 **2 Methods**

158 **2.1 Subjects**

159 The data analyzed in this paper are from the Ninapro database that includes electromyography data
160 related to hand movements of 78 subjects (11 transradial amputees, 67 intact subjects) divided into
161 three datasets. The Ninapro dataset 1 includes data acquisitions of 27 intact subjects (7 females, 20
162 males; 2 left handed, 25 right handed; age 28 ± 3.4 years). The second dataset includes data
163 acquisitions of 40 intact subjects (12 females, 28 males; 6 left handed, 34 right handed; age $29.9 \pm$

164 3.9 years). The third dataset includes data acquisitions of 11 transradial amputees (11 males; 1 left
165 handed, 10 right handed; age 42.36 ± 11.96 years). All participants signed an informed consent form.
166 The experiment was approved by the Ethics Commission of the state of Valais (Switzerland), and it
167 was conducted according to the principles expressed in the Declaration of Helsinki. More details
168 about the subjects are reported in the official database description (Atzori et al., 2014b).

169 **2.2 Acquisition setup and protocol**

170 *Acquisition setup:* Several sensors were used to record hand kinematics, dynamics and correspondent
171 muscular activity during the experiments. Hand kinematics were measured using a motion capture
172 data glove with 22 sensors (CyberGlove II, CyberGlove Systems LLC). A 2-axis Kübler IS40
173 inclinometer (Fritz Kübler GmbH) was fixed onto the wrist of the subjects to measure the wrist
174 orientation. Hand dynamics were measured using a Finger-Force Linear Sensor (FFLS) (Kõiva et al.,
175 2012).

176 Two types of double differential sEMG electrodes were used to record muscular activity. Dataset one
177 was recorded using ten OttoBock MyoBock 13E200-50 (Otto Bock HealthCare GmbH), providing an
178 amplified, bandpass-filtered and Root Mean Square (RMS) rectified version of the raw sEMG signal
179 at 100Hz. The amplification of the electrodes was set to 5. These electrodes were fixed on the
180 forearm using an elastic armband. Dataset 2 and 3 were recorded using 12 electrodes from a Delsys
181 Trigno Wireless System, providing the raw sEMG signal at 2 kHz. These electrodes were fixed on
182 the forearm using their standard adhesive bands and a hypoallergenic elastic latex-free band.

183 The sEMG electrodes are positioned in order to combine two methods that are common in the field,
184 i.e. a dense sampling approach (Fukuda et al., 2003; Li et al., 2010; Tenore et al., 2009a) and a precise
185 anatomical positioning strategy (Castellini et al., 2009; De Luca, 1997). Eight electrodes were
186 positioned around the forearm at the height of the radio humeral joint at constant distance from each
187 other; two electrodes were placed on the main activity spots of the flexor digitorum superficialis and
188 of the extensor digitorum superficialis (Atzori et al., 2015) (identified by palpation). In dataset 2 and
189 3, two electrodes were also placed on the main activity spots of the biceps brachii and of the triceps
190 brachii (also in this case, identified by palpation). More details about the acquisition setup are
191 reported in the official database descriptor (Atzori et al., 2014b).

192 *Acquisition protocol:* Data acquisitions were performed with two types of exercises. In the first one,
193 the subjects imitated several repetitions of hand movements that were shown on the screen of a
194 laptop in the form of movies. In the second one, the subjects repeated nine force patterns by pressing
195 with one or more hand digits on the FFLS. Several coloured bars on the screen guided the subjects to
196 increase the force exerted by each finger up to 80% of the maximal voluntary contraction force, and
197 then back to 0%. Intact subjects were asked to imitate the movements with the right hand, while
198 amputees were asked to imagine imitating the movements with the missing hand, as naturally as
199 possible.

200 The entire acquisition protocol included several repetitions (10 repetitions for dataset 1, 6 repetitions
201 for dataset 2 and 3) of 40 movements and 9 force patterns that were selected from the hand taxonomy
202 and robotics literature (Crawford et al., 2005; Cutkosky, 1989; Edwards et al., 2002; Feix et al.,
203 2009; Kamakura et al., 1980; Kato et al., 2006; Sebelius et al., 2005) also in relationship to the
204 activities of daily living (ADL). Movement repetitions lasted 5 seconds and were followed by 3
205 seconds of rest.

206

207 **2.3 Data Analysis**

208 Data analysis aims at classifying data into an average of more than 50 classes (corresponding to hand
209 movements) with convolutional neural networks and to compare the results with classical machine
210 learning techniques.

211 *Pre-Processing:* For both classical and deep learning approaches, the following steps were executed.
212 All the data streams were synchronized by super-sampling them to the highest sampling frequency (2
213 kHz or 100 Hz, depending on the used myoelectric electrodes) using linear interpolation. Since the
214 movements performed by the subjects may not be perfectly synchronized with the stimuli proposed
215 by the acquisition software due to human reaction times and experimental conditions, relabeling was
216 performed offline with a generalized likelihood ratio algorithm (Kuzborskij et al., 2012). Since the
217 Trigno electrodes are not shielded against power line interferences, their electromyography
218 measurements were filtered from 50 Hz (and harmonics) power-line interference using a Hampel
219 filter (Kuzborskij et al., 2012).

220 The test set consisted of approximately 1/3 of the movement repetitions (repetition 2, 5 and 7 in
221 database 1; repetition 2 and 5 in database 2 and database 3). The training set consisted of the
222 remaining repetitions. This approach is different from the leave-one-out approach used by Park and
223 Lee (Park and Lee, 2016).

224 For classification using convolutional neural networks, after several preliminary tests (aimed to better
225 understand the response of convolutional neural networks on sEMG), the Delsys trigno signals were
226 made similar to the Otto Bock's by Root Mean Square (RMS) rectification. Afterwards, the signal
227 was subsampled at 200 Hz, in order to reduce computational times. Then, (both for the Delsys and
228 the Otto Bock) the signals were low pass filtered at 1 Hz. Several normalization procedures were also
229 tested during pre-processing in order to augment the performance of convolutional neural network
230 classification, without leading to sensible improvement of the results.

231 *Classification using convolutional neural networks:* The convolutional neural network consisted of a
232 modified version of a well known convolutional neural network (LeNet) (LeCun et al., 1995),
233 according to the implementation suggested for Cifar-10 in the package MatConvNet (Vedaldi and
234 Lenc, 2015). The choice of a simple net, despite more complex recent ones being available, was
235 performed in order to accelerate the training phase and to allow evaluating the effects of several pre
236 processing, architectural and optimization parameters according to characteristics of the problem.
237 While convolutional neural networks have been applied to many fields including computer vision
238 and speech recognition, their application to sEMG data is relatively novel (Park and Lee, 2016).

239 The architecture of the convolutional neural network (Figure 1) was structured as follows. The input
240 data corresponds to time windows of 150 ms, spanning all the electrode measurements available (10
241 for the Otto Bock, 12 for the Delsys). This choice corresponds well to what is done usually in the
242 field, i.e. analyzing time windows aimed to allow control in real time (Atzori et al., 2014b; Englehart
243 et al., 1999).

244 The first block of the net is composed of the following parts. First it includes a convolutional layer
245 composed of 32 filters. After several tests including different shapes and sizes, the filters were
246 defined as a row of the length of number of electrodes. Second, it includes a rectified linear unit as
247 non-linear activation function.

248 The second block of the net is composed of the following three parts. The first one is a convolutional
249 layer with 32 filters of size 3×3 . The second one is a non-linear activation function (rectified linear
250 unit). The third one is a subsampling layer that performs average pooling with filters of size 3×3 .

251 The third block of the net is composed of the following three parts. The first one is a convolutional
252 layer with 64 filters of size 5×5 . The second one is a non linear activation function (rectified linear
253 unit). The third one is a subsampling layer that performs average pooling with filters of size 3×3 .

254 The fourth block of the net is composed of the following two parts. The first is a convolutional layer
255 with 64 filters of size 5×1 for the Otto Bock electrodes and size 9×1 for the Delsys electrodes. The
256 second is a rectified linear unit.

257 The fifth block of the net is composed of the following two parts.. The first one is a convolutional
258 layer with filters of size 1×1 . The second is a softmaxloss.

259 Several weight initializations were tested. Finally, the weights of the convolutional layers are
260 initialized with random values in ranges determined in percentage according to the data range, in
261 order to get reasonable training time and stability.

262 Hyper-parameters were identified via random search and manual hyper-parameter tuning (Bengio et
263 al., 2015) on a validation set composed of 2 subjects randomly selected from dataset 1 and dataset 2.
264 After several tests, the convolutional neural networks were trained using stochastic gradient descent
265 with momentum 0.9, the learning rate was fixed at 0.001, the weight decay at 0.0005, the batch size
266 was fixed at 256 and the number of epochs 30.

267 In order to increase accuracy, data augmentation was performed before training. In particular, data
268 were doubled and white Gaussian noise was added to the new set with a signal to noise ratio equal to
269 25 of the measured power of the signal. Several data augmentation tests were made on the validation
270 set, mainly changing the noise creation procedure. The selected method was chosen based on a
271 balance between improvement results and low computational time.

272 *Reference classical classification:* The procedure was based on the one described by Englehart et al.
273 (Englehart and Hudgins, 2003; Gijsberts et al., 2014). It consisted of windowing at 200 ms, feature
274 extraction and classification. Five signal features and three classification methods were considered,
275 according to previous application to the Ninapro sEMG database and to sEMG in general (Atzori et
276 al., 2014b; Englehart and Hudgins, 2003; Gijsberts et al., 2014; Kuzborskij et al., 2012). The selected
277 signal features include: marginal Discrete Wavelet Transform (mDWT), Histogram (HIST),
278 Waveform Length (WL), Root Mean Square (RMS) and the normalized combination of all of them.
279 The histogram (HIST) was divided into 20 bins along a 3σ threshold (Zardoshti-Kermani et al.,
280 1995). The marginal Discrete Wavelet Transform (mDWT), was created with a db7 wavelet with 3
281 levels (Lucas et al., 2008). The used classifiers are well known, having previously been applied on
282 sEMG in general and thoroughly described on the Ninapro data. They include: Random Forests
283 (Breiman, 2001), Support Vector Machines (SVM) (Cristianini and Shawe-Taylor, 2000) and k-
284 Nearest Neighbors (Duda and Hart, 2001). The classification is performed on all the movements
285 included in the database, including rest periods and the data are balanced according to the number of
286 repetitions of movements. The reference classification procedure is described in detail in Atzori et al.
287 (Atzori et al., 2014b).

288 **3 Results**

289 Data analysis aimed at classifying an average of more than 50 hand movements, meaning with an
290 average chance level lower than 2%. As described in detail in the discussion, the results can be
291 compared only with sEMG classification problems targeting a similar number of classes (e.g. (Atzori
292 et al., 2014b, 2015)). As previously shown (Atzori et al., 2016), results higher than 90% can be easily
293 obtained with similar approaches by reducing the number of classes, even on amputees.

294 As represented in figure 2, the classification accuracy obtained with convolutional neural networks
295 using the simple architecture proposed is comparable the average results obtained with classical
296 classification techniques, but lower than the best results obtained with classical classification
297 techniques.

298 The average classification accuracy obtained using the convolutional neural network on dataset 1 is
299 $(66.59 \pm 6.40)\%$. The average classification accuracy obtained using all the classical methods on this
300 dataset is $(62.06 \pm 6.07)\%$. The best classical classification method (Random Forests with all
301 features) obtained an average classification accuracy of $(75.32 \pm 5.69)\%$.

302 The average classification accuracy obtained using the convolutional neural network on dataset 2 is
303 $(60.27 \pm 7.7)\%$. The average classification accuracy obtained using all the classical methods on this
304 dataset is $(60.28 \pm 6.51)\%$. The best classical classification method (Random Forests with all
305 features) obtained an average classification accuracy of $(75.27\% \pm 7.89)\%$.

306 For amputees (dataset 3), the average classification accuracy obtained using the convolutional neural
307 network is $(38.09 \pm 14.29)\%$. The average classification accuracy obtained using all the classical
308 methods on this dataset is $(38.82 \pm 11.99)\%$. The best classical classification method (SVM with all
309 features) obtained an average classification accuracy of $(46.27\% \pm 7.89)\%$.

310 With convolutional neural networks (as well as with classical methods) the ratio between the
311 accuracy and the chance level is in general higher than in previous results described in the literature
312 for hand movement recognition in sEMG, e.g. 8.5 (10 movements, accuracy 84.4%, (Li et al., 2010)),
313 10.56 (12 movements, accuracy 87.8%, (Tenore et al., 2009a)).

314 The average time required to train each convolutional neural network was 1 hour and 42 minutes.
315 The average time required to test the network was 21.5 seconds using an Nvidia Titan-x GPU. This
316 leads to a time for the classification of each time window of less than 10^{-3} s.

317 Several network architectures, pre-processing parameters and hyperparameters were tested on a
318 validation set, composed of 3 subjects randomly selected from dataset 1 and dataset 2. Depending on
319 the case, the validation was made on all the movements available, or on a subset of 8 movements. A
320 summary of the results is reported in table 1. The table reports the minimum Top-1 errors obtained
321 for each parameter with the corresponding Top-5 error and epoch. Two different methods were
322 tested: "time window normalization" (i.e. subtracting to each time window the mean and dividing it
323 by the standard deviation) and "normalization based on training data" (i.e. subtracting to all the time
324 windows the training data mean and dividing them by the training data standard deviation). The best
325 results were obtained without any normalization procedure. Normalization procedures can affect the
326 classification error up to 37%. Changing the learning rate can strongly change the minimum error for
327 a fixed amount of epochs, while changes to the weight decay do not seem to affect substantially the
328 error. Finally, data augmentation can reduce the classification error up to 4% while also strongly
329 reducing the number of epochs requested to reach it. A strong reduction of the error rate (48%) was

330 obtained between the tests on normalization and the tests on the hyperparameters. This result was due
331 to changes in the architecture of the net, in particular considering the first layer.

332 In conclusion, the classification accuracy obtained with the proposed convolutional neural network is
333 strongly influenced by several factors (including network architectures, pre-processing parameters
334 and optimization parameters), it provides accuracy that is more precise than the average traditional
335 methods in extremely little time, but it does not replicate the best classical classification methods for
336 similar tasks.

337

338 **Table 1: Tested pre-processing parameters and hyper-parameters. The table reports the minimum Top-
339 1 errors obtained for each parameter with the corresponding Top-5 error and epoch.**

	Top-1 error	Top-5 error	Epoch
1. Normalization (8 movements, different net)			
No Normalization	0.6	0.26	150
Time window normalization	0.97	0.88	200
Normalization based on training data	0.65	0.32	100
2. Learning Rate (8 movements)			
0.001	0.12	0.01	80
0.01	0.88	0.37	80
0.05	0.88	0.37	80
3. Weight decay (8 movements)			
0.0001	0.12	0.01	80
0.0005	0.12	0.01	80
0.00005	0.12	0.01	80
4. Data Augmentation Gaussian Noise SNR Ratio (all movements)			
0	0.23	0.65	75
0.5	0.22	0.71	50
5	0.21	0.05	75
15	0.21	0.21	75
25	0.19	0.045	25
35	0.22	0.065	40
45	0.21	0.049	52
55	0.21	0.056	75

340

341

342 **4 Discussion**

343 During the last five years, deep learning and convolutional neural networks revolutionized several
344 fields of machine learning, including speech recognition and computer vision. Thus, it seems
345 reasonable to think that they may improve the analysis of surface electromyography and contribute to
346 bridge the gap between prosthetics market (that requires fast and robust control methods) and recent
347 scientific research results in rehabilitation robotics (that show that dexterous and proportional control
348 is possible).

349 In this paper we introduce a baseline for the application of convolutional neural networks to the
350 classification of hand movements by sEMG and we compare the results with a set of classical
351 machine learning methods on a large set of movements and subjects (including also amputees).

352 The electromyography data of 67 intact subjects and 11 hand amputees performing an average of
353 more than 50 hand movements were analyzed. The data are publicly available on the Ninapro
354 database (Atzori et al., 2014b) and they are divided into three datasets including respectively 27, 40,
355 and 11 subjects.

356 The results show that convolutional neural networks with a very simple architecture are comparable
357 to the average classical machine learning classification methods and they show that several factors
358 (including pre-processing, the architecture of the net and the optimization parameters) are
359 fundamental for the analysis of surface electromyography data. Convolutional neural networks
360 results obtained with the very simple architecture described in this paper are not worse than the
361 average of classical methods, thus we believe that they are a good avenue to explore.

362 The classification accuracy obtained with convolutional neural networks using the proposed
363 architecture is $(66.59 \pm 6.4)\%$ on dataset 1, $(60.27 \pm 7.7)\%$ on dataset 2 and $(38.09 \pm 14.29)\%$ on
364 amputees (dataset 3). The average results are comparable to the average results obtained with the
365 reference classical classification, but lower than the results obtained with the best classical
366 classification techniques. The results described in this paper represent one of the first attempts to
367 train a simple convolutional neural network on sEMG data. The literature for computer vision and
368 object recognition showed that larger networks can achieve higher accuracy on complex tasks
369 (Bengio et al., 2015). Thus, it may be interesting to evaluate if larger networks can improve sEMG
370 classification too.

371 Regarding the overall accuracy (obtained both with convolutional neural networks and the reference
372 classical methods), it is fundamental to note that the results should be compared only with analyses
373 considering a similar number of classes, i.e. approximately 50. The chance level varies with the
374 number of classes. Therefore, considering a dataset (with a specific number of samples), feature and
375 classifier, classification accuracy is expected to decrease when the number of classes increases (Deng
376 et al., 2010a). Thus it is fundamental to compare accuracy only when the number of classes is
377 comparable. It is common to see in the literature movement classification accuracy of up to 90-95%
378 (Castellini and van der Smagt, 2009; Li et al., 2010; Peerdeman et al., 2011b; Tenore et al., 2009b).
379 However, most of these studies consider between 4 and 12 movements, with chance level between
380 25% and 8.33%, while the chance level of this study is inferior to 2%. Thus a comparison of the
381 accuracy would not be reasonable and justified by statistics. As previously shown, results over 90%
382 of accuracy can be obtained reducing the number of classified movements to approximately 10 for
383 amputees, even starting from lower classification accuracies (Atzori et al., 2014a, 2016). Moreover,
384 classification accuracy can change strongly depending on several other parameters (including e.g.

385 class balance and for amputees, several clinical parameters including forearm percentage, phantom
 386 limb sensation and years from the amputation (Atzori et al., 2016)). Therefore, comparisons in this
 387 field must not be made lightly.

388 Pre-processing, net architecture and the optimization parameters seem to be fundamental for the
 389 analysis of sEMG data with convolutional neural networks, since they can strongly change the final
 390 classification accuracy in the validation set, and time to converge. The factors that influenced the
 391 most the results were the shape of the first layer of the network, the initial weights of the layers, data
 392 augmentation procedures and the learning rate.

393 The net architecture that was chosen is extremely simple. This choice was made on purpose, in order
 394 to make it easier to evaluate the effect of changes in the pre-processing, in the architecture of the net
 395 and in the optimization parameters. However, more complex net architectures do exist and can be
 396 trained on sEMG data, thus probably leading to higher accuracies. This fact is extremely promising
 397 for the future of sEMG data analysis and rehabilitation robotics, and may lead to increase dexterous
 398 control robustness, thus contributing to bridge the gap between the prosthetics market and scientific
 399 research.

400 In conclusion, the baseline results that have been presented in this paper show that convolutional
 401 neural networks with very simple architecture can produce accuracy results comparable to the
 402 average classical classification methods, and they suggest that further studies may lead to improve
 403 the overall field of sEMG controlled dexterous hand prosthetics.

404

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457 [s.nips.cc/paper/4169-phone-recognition-with-the-mean-covariance-restricted-boltzmann-](http://papers.nips.cc/paper/4169-phone-recognition-with-the-mean-covariance-restricted-boltzmann-machine)
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Figure 01.JPEG

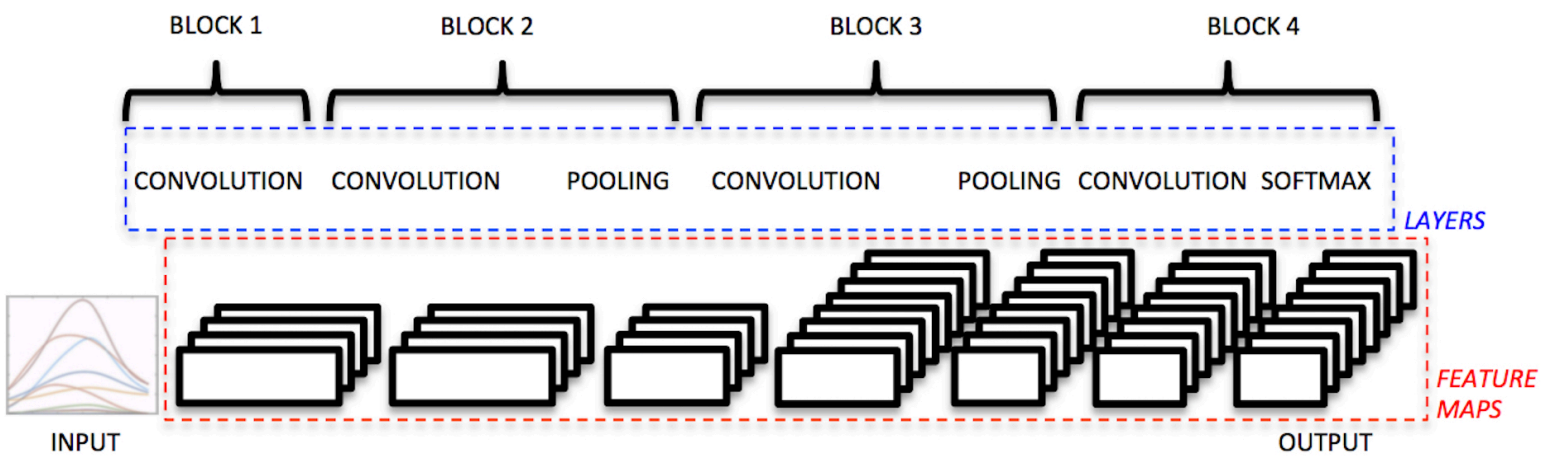


Figure 02.JPEG

