# Towards inter-session hand-gesture classification

A review on the state-of-the-art of the challenges and technologies using EMG

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## ABSTRACT

This review is an extension to the survey conducted by Adrian Spurr in 2015 [58] on using electromyography (EMG) signals in machine learning algorithms with a focus on HCI and hand pose estimation. This paper gives a broad overview of what has happened since 2015, but will partially overlap with contents presented in Spurr's survey. As such, the following is a copy of the abstract of Spurr's paper: "This paper serves as a survey for using electromyography (EMG) signals in machine learning algorithms, with a focus on HCI and hand pose estimation. It gives an overview on the current applications and issues which have been tackled, lists problems occurring when using this type of input and names a series of open questions which have not been sufficiently addressed or solved in a satisfiability manner. It ends with a proposal for a novel feature for approximating continuous hand pose with EMG, motivated by the current literature available. . . "

**Keywords:** surface Electromyography, high-density EMG, cross-session, hand-gesture classification, active prosthetics, HCI

## PROPERTIES OF sEMG SIGNALS

Electromyography (EMG) sensors record electrical signals formed by muscles that originate from the peripheral nervous-system. Raw sEMG signals have peak-to-peak amplitudes of 0-2mV, rising up until 10mV [59] with a band frequency ranging between 0-1000Hz [57]. However, the band frequency carrying the most information lies between 20-500Hz according to [11] [36], or even just between 50-150Hz according to [59]. sEMG signals are time and subject varying because of muscle fatigue, muscle length, muscle fibre architecture and level of effort [36] [48], as well as electrode shifts, changes in arm-posture and slow time-dependent changes such as electrode-skin impedance [12] [21]. As such, a normalized sEMG amplitude is often obtained through non-linear division by a Maximum Voluntary Contraction (MVC) measure of the respective test subject [9] [41]. The MU firing rate also follows a non-linear law [40] and the number of MUs activated is determined by the power of the muscle contraction [52]. There is an uncertain relation between EMG signals and muscle application [15]. sEMG signals are time dependant [36] and due to the mentioned reasons above believed to be stochastic [53] [55][60] [14].

## NOISE SIGNALS RESULTING FROM EMG MEASUREMENT (NAZMI et al. 2016)

There are two main issues that influence the fidelity of the signal. The signal-to-noise ratio examines the ratio between the energy in EMG signals to the energy in noise signals. Yet another problem are pure noise signals, of which there are different categories:

*Inherent Noise in Electronics Equipment* in EMG Signals is caused by electrical equipment. Electrodes made of silver (Ag) and silver chloride (AgCl) however are found to give an adequate signal-to-noise-ratio (SNR) and are electrically very steady. Furthermore, bigger electrode sizes imply decreased impedance. Generally, this type of noise can be eliminated using intelligence circuit design and high quality instruments [48].

*Ambient Noise* is 1-3 times bigger than the EMG signal of interest, which includes Power-Line Interference (PLI) arising from the 50-60Hz spectrum. A high pass filter can remove the interference if the frequency of the interference is high [48]. This is the most common kind of noise [59].

*Motion Artifacts* are caused by moving muscles, skin and spread of the innervation zone (IZ) electrode displacement [54] [13] [42]. Blood flow can also be a factor [39]. These can be reduced by proper design and setup of the system. Band pass filters accepting a frequency between 20-500Hz can also reduce these significantly [5] [19].

*Inherent instability of the signal* is caused by the stochastic nature of the EMG signals [13]. Because this signal is unstable, it can be regarded as unwanted. The signal usually lies within the frequency range of 0-20 Hz [48], but can potentially be accepted without a de-noising structure within the system.

*Electrocardiographic (ECG) Artifacts* arise due to an overlap of ECG and EMG frequency spectra and their shared characteristics such as non-stationarity and varying temporal shape [54] [13]. It is very difficult to remove ECG [48]. However, if ECG can be effectively measured, this signal could be subtracted from the EMG signal. Bandpass filters and mathematical morphology operator (MMO) appear to bring acceptable results. [1] [48].

*Cross-Talk* arises when signals from nearby muscles, which are not in the monitored muscle group, are recorded by the electrode [13]. Setting the IED to 1-2cm, and carefully adjusting the radius of the electrode can effectively reduce this noise [48].

There is no generally applicable de-noising strategy. As such, de-noising is application-specific.

## MATHEMATICAL MODEL OF MEASURED EMG SIGNALS

There are hypothesis for different mathematical models that describe EMG signals. However, simulating models lack realism, especially when simulating the MU firing rate, as well as the force generating phases [2]. Some refer to probability density functions that can describe the amplitude of EMG signals [61] [47]. The classification accuracy increases when the signal is measured in a time-window of length 128-500ms [22][61] [43]. The resulting model heavily depends on the electrode positioning [48], so there is a discrepancy between measured values and real values. Although the EMG signals are believed to have a reproducible [18] stochastic nature [55] [60] [14], the investigated literature does not show consensus among the chosen Probability Density Function (PDF) of the signals [48]. Although the central limit theorem proves that any dataset can be modelled as a normal distribution, it has been shown that the distribution of EMG generating signals is not a Gaussian one. This is because the actual signals are skewed towards zero [29] [8].

## PARAMETERS FOR ELECTRODES (Kilby, Prasad, and Mawston 2016)

The following paragraphs enumerate and discuss common variables in electrode-placement.

*Electrode Design and Configuration* Electrode materials that are used most often include pre-gelled silver (Ag) or silver chloride (AgCl). For dry configurations, no preference is detected [35], but similar performance to gelled electrodes are shown [44]. Shapes are of minor significance. SENIAM, a recognized European research organization association that substantially studied and researched in the area of sEMG, has recommendations on the setup of cables, electrodes and a possible pre-amplifier [35]. Increasing the number of electrodes increases accuracy, but this effect plateaus quickly after 100 placed electrodes [3].

*Data Acquisition of sEMG signals* include sampling frequency and bit-resolution of the data acquisition card [35].

*The choice of monopolar, bipolar, single-differential or double-differential* is another parameter to be set, especially in the case of grid-like structures. Usually an electron put on a bony area is used as a ground-signal. As such, studies are also conducted on the placement of the electrodes relative to the innervation zones (IZ) and tendon zones (TZ) [7] [6]. Monopolar detection provides the maximum information, but also includes fiber end effects, while bipolar detection provides a clear picture of any innervation and tendon zones. However, double differential detection is the most suitable for estimating the muscle fiber conduction velocity [35].

*Signal Pre-Processing of sEMG signals* [35] can include simple bandpass/butterworth filters [] and signal amplifications [].

*Factors in the testing of the subject* include the muscle-specific deviations, the experimental set-up, and the placement of the electrodes on the skin surface [35]. Sometimes, small muscles might have a high impact on the gesture formed, but might not produce high-enough threshold levels to be detected [44]. Possibly, this is caused because these muscle are too deeply located [19].

Generally, the procedure of placing the electrodes on the skin is a topic that is not much discussed in current literature [35] [24]. Again, these factors are algorithm- and application-specific. See appendix A for a list of manufacturers.

## COMMON FEATURES USED [48]

Features can be divided into time-domain (TD), frequency-domain (FD) or time-frequency-domain (TFD) [62] [27] [20] [48]. The following will discuss the most often used feature. The reader can refer to [48] for a table of features used in previous papers. None of the features selected seem to be an automated choice [48].

*Root mean squared (RMS)* [31] [48] is a TD-feature that is often used with bipolar single EMGs, showing a correlation between the force generated by the muscle and the number of activated Muscle Units (MUs) []. For sEMG grids, experiments often average over multiple time frames of sEMG frames to receive one instantaneous image. RMS appears to be the most applicable and accurate parameter, as it provides an accurate measure for raw muscle activity [48].

*Mean Frequency (MNF) and Median Power Frequency (MNP)* are FD-features and are often used to characterize EMG signals, especially for muscle contractions [45], or to characterize fatigue over time [51]. However, different MUs have different recruitment thresholds, and thus must be considered differently [38] [37] [48].

Time-Frequency-Domain (TFD)-features can either be novel features or be ensembled from the above mentioned TD and FD features [25]. These features, however, heavily suffer from the curse of dimensionality [9], which can be reduced through dimensionality reduction techniques [48] or potentially finding an optimal embedding layer. However, it is shown that leaving certain, apparent insignificant information, can decrease the classification accuracy of gestures. [add this to the discussion rather maybe?]

## GRID-CONFIGURATIONS OF sEMG SIGNALS [35]

There are different types of grid-configurations for array-shaped sEMGs. A combination of different configurations, for example 8 linear arrays put around the forearm is also possible. Sizes in arrays usually differ greatly but are between 1-10mm, either circular or elliptical in shape. SENIAM has no suggestions for the inter-electrode-distance (IED) in grids yet, but past experiments show that values between 2.5-20mm are common [35].

*Linear Array Electrodes* can use monopolar, bipolar and single (or more) differential configuration. These are often stacked together columns wise into an arrays.

*2D Array Electrodes* usually produce monopolar signals which are then further processed for analysis [35].

*HD-sEMG* are generally electrodes that are uniform in two spatial axes and densely distributed. 2D multi-electrode configuration exhibit higher signals and lower cross-talk compared with other types [16]. An intended consequence of bipolar and higher-order montages, and of a short IED, is the suppression of the far-field activity [35].

*HSR-sEMG electrodes* usually record monopolar signals and process these through a convolution weight matrices (usually 4 for and -1 for neighboring pixels). This is equivalent to the Laplace operator and approximates second-(or higher)-order differentials. Applied along the fiber direction, this can also approximate conduction velocity, and determine the location of innervation zones and tendons.

### COMMON PRE-PROCESSING METHODS

Most studies don't put much detail into the pre-processing stage, but it has repeatedly been shown that Butterworth filters with a cut-off frequency of 20-500Hz have been used [11] [36]. However, this 'noise' might also include useful patterns [23], and should be removed with care. Alternatives are bandpass filters with frequencies of 5-322Hz [59] or 20-380Hz [18]. Power-Line interference might be removed using a band-stop filter (45-55Hz second order Butterworth) [18]. The signal might also need to be converted from analogue to digital through a ADC converted [59]. Segmentation techniques are relative to the application. It is open to discussion, if adjacent or overlapped windowing techniques are preferable [48]. As always, finding the optimal features is also an open question, but there exists a preference.

### HAND CLASSIFICATION MEHOTDS USING EMG SIGNALS

Some major work has been done in the field of within/intra-session (test and training-data taken from within one session and one subject), hand gesture classification. The majority of the work has been done in classification, while there also exists work in continuous estimation [19]. Some common algorithms that have shown good results include:

- **Linear Discriminant Analysis (LDA)** is being deployed after using PCA to reduce to input feature set with a classification accuracy of 93.75% for [ number of gestures] different gestures [cite actual papers] [48].
- **Multi-Layer-Perceptron (MLP)** is being used achieving 99% accuracy for 6 different hand gestures to be classified [34] [48].
- **Fuzzy Logic (FL)** classifies the stages of contraction (start, middle, end) with 97% accuracy [cite actual papers] [cite number of gesture] [48]. Neuro-Fuzzy systems are an extension to this [32].
- **Ensemble techniques** using multiple feature sets even achieve 98.87% classification accuracy [look how many different hand gestures were included] [cite actual papers] [48].
- **Support Vector Machines (SVM)** is being deployed to classify instantaneous frames from sEMG measurement [56], or are sometimes ensemble with pressure sensors (FSR) to also include wrist [44] or forearm [] motion. For included pressure sensors, the accuracy ranges between 97.5% for wrist gestures and 94.0% for finger gestures classifying between 14 gestures. For inertia sensors the accuracy ranges between [must look this up again, should be in the IMU paper].
- **Deep Convolutional Neural Nets** can be used in ensemble over 40 frames at 1000Hz, using simple majority voting to get classification accuracies of over 96.8% for over 40 gestures [23]. Apparently, 150ms is the windows size suggested to consider, to classify a gesture [23]. All this is possible because the HD-sEMG can be considered as an imaging tool [46]. It is also reported that usually we have 8-11 firing MUs per second [41] which might satisfy why recordings of 100ms is needed.

Funnily, some algorithms, such as the Fuzzy Logic system, improve when the number of output classes are increased [19]

Some work has also been done using ultra-sound sensors to help the EMG classify gestures. However, motions are sometimes detected through ultrasound before sEMG signals are produced. This could either be a bug in the calibration process, due to the algorithms, or because initial bursts were ignored [15]. Some extensive studies have been done, correlating with ultrasound sensors, showing that different time-windows should be considered when classifying an EMG signal [15].

### APPLICATIONS OF INTER/CROSS-SESSION sEMG

We will present challenges that must be overcome to solve the cross-session problem, and show past approaches that tried to solve this problem. Although (auto-)calibration features are desirable [3], little work has been done on cross-session sEMG measurements, so [41] to find papers that included cross-session application, papers that included the term "days" or "weeks" were taken into consideration.

#### Challenges

Often, different subjects have different muscle structures with which some muscles are more visible to the device than others. [41]. A benchmarking dataset is missing, and the biggest one contains 23 participants with [number of gestures] gestures each [18]. The common problem of inter-subject, and even in cross-session, sEMG measurements is the high subject-specifity and high variability of the attained data [12] [21]. A negative correlation between the body-mass-index and gesture classification accuracy is noted [4] [28].

#### Approaches

Often, some kind of initial calibration [56] or a reference to a relaxed state [15] is used in cross-session settings. Amma et al. [3] pioneered auto-calibration, and a first end-to-end model has been created [18], but the problem of cross-session hand gesture classification is still an open one. Both presented models recorded sEMG frames over time, and the appropriate output label. A list of datasets can be obtained in Appendix B.

Amma et al. [3] tried to measure sEMG in cross-session using a single calibration gesture. For this, he used a bony-area as a reference to shift the resulting sEMG image for calibration. The recognition of the bony-area is only approximated by the area of lowest muscle activity, and found through the watershed algorithm. Another method he used was a Gaussian Mixture Model (GMM) in 2 dimensions, which would identify areas of high activity, and shift the sEMG image accordingly. RMS was used to detect muscle activity, and the data is interpolated using bicubic interpolation. These methods resulted a calibration method with 75% accuracy in hand gesture classification.

[18] trained a deep Convolutional Neural Net (CNN) using domain adaption [49] techniques. These techniques rely of fine-tuning pre-trained networks [17] . An algorithm that is being used is AdaBN, making the network more robust to inconsistencies in the covariance of the covariance data. AdaBN is similar to batch-normalization, which subtracts the mean and divides the standard-deviation from the incoming layer [but accuracy in here]

$$v = \frac{(u-\mu)}{\sigma} \times \gamma + \beta$$

with the parameters $\gamma$ and $\beta$ to be learned. This is regraded as an unsupervised method which does not require labeled sEMG data. During training, it must be ensured that the entire batch stems from the same session and same subject, otherwise, the learning parameters gamma and beta cannot be effectively learned. This model achieved state-of-the-art in cross-session with about 80% accuracy. The auto-calibration takes about 10 seconds to take place.

Other work has also been done, but was less successful [50] [30] [33], showing that domain adaption techniques might be a viable option. Data augmentation [26] [10] and model adaption techniques [3] [50] [30] [33] have been devised for this. Due to the high subjectivity, the problem of cross-session hand gesture classification can be regarded as a multi-source domain adaption problem [49].

## DISCUSSION

To produce a wristband that can accurately classify hand gestures, a predictive model needs to be created. The problem of creating this pre-trained model can be regarded as a supervised learning task. This pre-trained model can then be used as a starting point, from which calibration for individual subjects can automatically take place, potentially through unsupervised learning.

### Future fields for research

Further research could be conducted in the following domains:

*Image and Video classification:* is a viable path, for the reason that the sEMG signal produced is a 2D matrix of one-dimensional color-values, and as such, is resembling an image. Video classification is viable as well, because the sEMG signal produced is a time-dependent sequence, and due to the stochastic nature of the signal, multiple consecutive frames must be regarded to draw conclusion.

*Domain Adaption* is a possible research field, as it is believed that changing sessions / subjects just shift the classification task in space. This means that the problem is the exact same one, just shifted in the problem domain. If enough different domains can be covered in the training data, the domain adaption problem can be easy. If unlabeled data is present, domain adaption techniques could give the small necessary push needed to realize cross-session hand-gesture classification.

*Zero-Shot-Learning* is a field close to domain adaption, but deals with minor or no labeled data. The goal is to achieve a high-enough learning effect given sparse data to draw personalized quality. This is interesting, because it is possible to get unlabeled data from the user: If it is possible to use this unlabeled data to improve the quality of the calibration, it might be possible to generalize between sessions, and potentially subjects.

*Methods for hand gesture classification* are interesting because some methods might generalize well to cross-session or cross-subject settings.

Generally, any other domain looking at the problem of auto-calibration might be useful in bringing new ideas.

### Possible next steps

*Increasing the dataset size:* It is often mentioned that increasing the number of data samples fed to a model will increase it's accuracy, assuming the trained model has a high-enough capacity. As such, increasing the number of samples collected for a given gesture should result in an increased accuracy. Apart from that, it is assumed that there exists a finite number of different muscle types that the model has to adapt to. The dataset with the highest number of different subjects is the NinaPro dataset with about 30 subjects. However, 30 different samples is usually regarded as too little data for deep models. As such, it would make sense to create a dataset that includes a higher number of different sessions ( 100), and then potentially expand to having a higher number of different test subjects.

*Have non-mobile/ classification measure:* If it is possible to set up an effective classification measure which can be used naturally for many hours, much more training data can be collected. However, it should be noted that the current training data should vary in the number of sessions/subjects involved, not necessarily number of gestures occurring. Also, any other armband-internal system that collects data or concurrently improves the classification accuracy of the armband can help. (such as the 2-segment armband, where segment 2 helps classify it, and the neural net is actually trained/backpropagated on segment 1)

### Models that could potentially work in classifying cross-session

*CNNs with a combination of LSTMs or Residual/Highway Layers:* As above mentioned, the task of classifying EMG signals is similar to the task of image classification. CNNs are the most popular choice in computer vision tasks, making the trained model resistance to small perturbations in the image. It is also important to regard the EMG signal as an integral sequences to classify the EMG images. LSTMs are the most popular choice in sequence-processing tasks and can capture long-term dependencies of currently up to 256 sequence-elements effectively. One could use CNNs to condense the momentary image into a hidden feature vector that represents the image. This hidden feature vector could then potentially be passed through a layer of LSTMs or through a residual/highway layer for sequence analysis.

*A deep architecture within an adaption algorithm:* Domain adaption algorithms have shown to improve the accuracy of the model. However, these algorithms must be fed with some well-chosen feature-vectors. Within the field of reinforcement learning, deep models are used to approximate the state-space (feature-vectors) and incorporate these results within tabular algorithms. A deep model could also be used in this case to classify gestures, and proven model adaption algorithms could be used to translate or calibrate the gestures.

*Wide and Deep Nets:* EMG signals have a part that can be generalized to all users, but also rely on personalization. An alternative to choosing domain adaption algorithms is to use Wide and Deep Nets. Recommendation systems that generalize but also personalize have a deep and wide architecture that acts similar to an ensemble, except that backpropagation starts from the same end (one unified model). Any other architecture that includes a part that personalized, and a part that generalizes could be optimal.

### Appendix A: Manufacturers list

- Electrodes, mainly for linear arrays: LISiN-Specs Medica, Italy (Kilby, Prasad, and Mawston 2016)
- ActiveOne, BioSemi, Amsterdam, Netherlands (Kilby, Prasad, and Mawston 2016)
- Shinystone, LogOnU Inc. (Kim, Kim, and Kim 2016)
- Inertial Unit: IMU EBIMU24GV2, E2BOX Co. (Kim, Kim, and Kim 2016)
- Wireless SHIMMMER EMG (Sulaiman et al. 2016)
- SPES Medica, Salerno, Italy (Martinez-Valdes et al. 2016)
- ADC: EMG-USB 2, 256-channel EMG amplifier, OT Bioelettronica, Torino, Italy (Martinez-Valdes et al. 2016)
- Delsys Trigno Wireless EMG (El-Khoury et al. 2015)
- OT- Bioelettronica (Amma et al. 2015)

### Appendix B: Available datasets that include cross-session data

- NinaPro - Sparse hand prosthetics dataset [18]
- CSL-HDEMG - Near-to-realistic dataset [number of subjects and gestures] [3]
- CapgMyo - 23 participants and [number of gestures] gestures to classify [18]

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