Application of Riemannian geometry to sEMG signal

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Abstract

Surface electromyography (sEMG) control methods of bionic mechanic hand became a medical and economic issue which made possible to conduct large research in acquisition tools and signal processing. There are sEMG classification methods providing good classification accuracy but the problem of robustness in cross-subject condition remains. Recently a new framework based on the Riemannian geometry has showed promising results in brain computer interfaces (EEG signals). This paper introduces the first use of this framework for sEMG data with naïve electrodes positioning. In one subject condition, the classification accuracy is >97%. In cross-subject condition the accuracy is about 69%. The Riemannian method always exceeds the standard discriminant analysis approach. These results show that the framework fit well with EMG data and is a good candidate for muscle machine interfaces.

Keywords : Riemannian geometry, machine learning, electromyography, covariance matrices.

I. Introduction

The surface EMG provides measures of the muscles electric activity via electrodes placed on the skin. When electrodes are on the arm muscles one can measure the activity of the muscles during different hand movements. Using this information enables the classification of the EMG signals which in term can be used to drive a fully integrated prosthetic hand, giving to patients the possibility to recover some of their capacities after the loss of a hand. Another application of this ongoing research is machine control in the broad sense. Indeed, different ways are are followed for controlling machine by motion: video acquisition as we

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can see in the case leap motion or kinect (Weichert et al., 2013) or EMG. Leap motion is accurate but it needs an external device and has a space constraint.

Several methods are currently used to perform the classification of sEMG signals. Linear discriminant analysis (LDA) and support vector machines (SVM) are the most popular. Alkan and al. (2012) show that SVM, associated to discriminant analysis, can perform a classification for four hand movements with very good average accuracy rate(99%) and error rate 1%. Mayer et al. (2008) achieved to classify 8 class (motions) with >98% accuracy on offline data and >94% on on line data (10 electrodes). They also show that the classification rate decreases as the number of class increases or decreases the number of electrodes. A mixed LDA and Principal component analysis (PCA) succeeded to classify five hand motions (hand closing, hand opening, index finger pinching, middle finger pinching and hand relaxing) with an accuracy of 98.8 (Zhang et al., 2012).

In recent year, researchers have been investigating a new classification framework for Brain Computer Interface (BCI) based on the Riemannian geometry in the manifold of covariance matrices. This method allows a high classification accuracy in several BCI paradigms such as Motor Imagery or P300 (Congedo, 2013). This approach involves a simple classification algorithm with little pre-processing, it is resistant to noise and cross-subjects variability. This is why we thought that Riemannian framework classification should be investigated on sEMG signals. The covariance matrix of sEMG signal epochs belongs to the manifold a of symmetric positive-definite (SPD) matrices and contains all the spatial information. Riemannian geometry provides as with an appropriate framework to manipulate SPD matrices. The aim of this article is to investigate this method with surface electromyographic data.

II. Methods

I. Subjects

The sEMG data were collected from six able-bodied participants (three males and three females, 22 to 26 years old, age mean 23.5, standard deviation 1.37). Before the experiment, they were informed about the protocol: the position of the body and the motions to do.

II. Experimental protocol

Data acquisition was performed via Biopac MP150 (BIOPAC Systems, Inc, USA). 10 Ag-AgCl electrodes were used with 2000 Hz sampling frequency. The participants were instructed to perform 12 classes of motions (thumb flexion, thumb extension, index flexion, index extension, opening hand, closing hand, hand extension, hand flexion, pronation, supination, grasp with index thumb, rest). For each class 20 trials were recorded. The experiment lasted 20 minutes and the acquisition was continuous. Participants were told to stand up and point the right arm, on which are placed the electrodes, to the ground. In this way electrodes were not disturbed by the contact with a support.

Figure 1: *Position electrodes with palm down.*

III. Electrode placement

We don't perform an optimization of the placement of the electrodes. For this study 10 electrodes were placed (6 proximal and 4 distal) so that anyone with no specialized knowledge of the arm anatomy could place them in the same way: measure the size of the arm, separate into 3 tiers, 4 electrodes placed around the arm to the limit of the first third of the starting poignant then do the same with 6 electrodes on the second third, avoiding placing electrodes on a radius or ulna (figure 1 and 2).

Figure 2: *Position electrodes with palm up.*

IV. Data segmentation

The problem of the segmentation (detection of the onset and offset of a trial) of sEMG signal is part of ongoing research (Kaur et al., 2009). To resolve this issue we chose to establish an experimental protocol to guide the subjects with a visual feedback displayed on a screen. The application shows to the subject the motion to be performed, the duration of the motion and the duration of the rest period. Every trial lasted 3s and after each one subject can rest for 2s (figure 3).

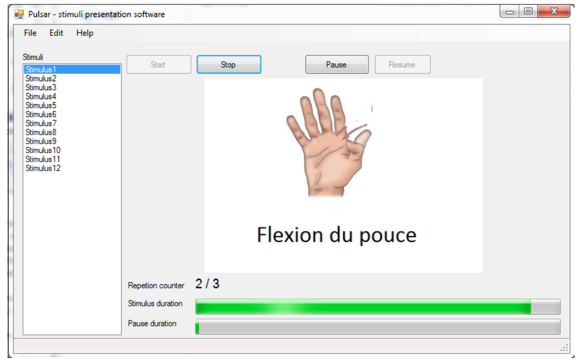

Figure 3: *Pulsar interface : application to guide the subjects. The first progress bar indicates the motion duration. The second indicates rest duration. In the middle, a picture presents motion to produce.*

In parallel to the acquisition of the 10 sEMG channels, two channels were added as trigger. The application sent a signal to one of these channels at the beginning and at the end of each trial. Another signal was sent to the second channel flagging a class change. The segmentation is then based on these two added channels.

V. Preprocessing

The most informative frequencies of sEMG signal are contained in the range of 20-700 Hz (Chen et al., 2011). Such pass band filter was applied to this range as well as a nochfilter at 50 Hz. These are the only preprocessing applied here.

VI. Classification method

In this section we describe the Riemaniann framework used to perform classification based on the covariance matrix of the signal. Note that this framework is not devoted to sEMG signal and can be applied to other data as well.

Given a trial data matrix X comprising N channels (in raws) and T samples (in columns), the covariance matrix is estimated by :

$$C = \frac{1}{N-1} X X^T. \tag{1}$$

The result is a SPD square matrix of dimension N*N where N is the number of channels. The matrix contains in diagonal elements the information about the energy of the signal and in non-diagonal elements the spatial information, i.e., the covariance between all electrodes taking pair-wise.

Given a number of training trials X for each class $z \in 1..Z$ corresponding to a hand motion, we estimate for each one its covariance matrix. The Riemannian framework provides a way to define an appropriate distance measure and geometric mean between covariances matrices respecting the particular structure of them (BARBARESCO, 2009). In this way, the computation of means and distances are more accurate and robust as compared to equivalent measures in the Euclidian space.

One of the differences between working in a Riemannian and Euclidian space is that the operations in Riemannian manifold are always local and are made with respect to a reference point (Congedo, 2013). Distance between two SPD matrices $P1$ and $P2$ with dimension $N * N$ is given by :

$$\delta(P1, P2) = [\sum_{n=1}^{N} log^2(\lambda_n)]^{1/2}, \tag{2}$$

where λ_n are the eigenvalues of $P1^{-1}P1$ and log^2 denotes the square of the log of the argument. Note that the dimensions of covariances matrices is the number of channels of the signal. In term of geometry, if we consider the covariance matrices as points in a curved space, this distance is the length of the shortest geodesic linking them.

With the definition of Riemannian distance we can compute the Riemannian geometric mean between M SPD matrices $P_1, P_2, ..., P_M$ as the SPD matrix G satisfies the following :

$$\underset{G}{argmin} \sum_{m=1}^{M} \delta^2(P, P_m) \tag{3}$$

There is no closed-form solution to compute the geometric mean but an iterative algorithm can find the unique minimum :

Algorithm 1 Geometric mean of M SPD matrices

Entry : Geomtric mean G of M SPD matrices $G = P_1, P_2, ..., P_M$ and t>0

1) Initialize G with the arithmetic mean : $\frac{1}{M}\sum_{m=1}^{M} G_m$

2)

repeat

$G = G^{1/2} exp[\frac{1}{M}\sum_{m=1}^{M} ln(G^{-1/2}P_m G^{-1/2})]G^{1/2}$

until convergence

$||\sum_{m=1}^{M} ln(G^{-1/2}P_m G^{-1/2})|| < t$, where $||\sum_{m=1}^{M} ln(G^{-1/2}P_m G^{-1/2})||$ is the Frobenius norm of the argument.

The principle of Riemannian framework have been summarized such as :

X is a set of trials in classes $z = 1...Z$ (training data). After preprocessing, calculate for each trial an estimation of the covariance matrix with which we can estimate for each class the Riemannian mean of these matrices. For new unlabeled trial, calculate its covariance matrix and then its Riemannian distance to the Riemannian mean of covariance matrices of each labeled class. Label the new trial with class with the smallest distance. This simple classification method is called MDM (Minimum distance classifier) (Congedo, 2013). In this way, spatial information can be used to perform a classification. The matrices contains also the amplitude informations of the signal but because the amplitude of EMG signal is stochastic, this information is not useful in state. Barachant and al. (2013) showed that it is possible to include frequency information. Our motivation is knowing if including frequency information could increase the classification rate of MDM (see theory part and results) for offline sEMG data.

VII. Frequency information

There is way to include frequency information in the MDM classification by applying pass-band filters to the signal. We use the method that have already been applied to the detection of P300 (Barachant et al., 2013) : Y pass-band filters are applied to all the X labelled trials in frequency ranges we know that contain information. That produces Y*X new trials to which is computed the covariance matrix. For new unlabelled trial we apply the same filters. After that we sum the Riemannian distances between the Y covariances matrices of the filtered new trial and the Y*Z means of the labelled trials. The minimum sum gives the label where to put the new trial.

The general method is summarize by algorithm 2.

Algorithm 2 MDM frequency algorithm

Training : trials Xz with Yz labels

Test : unlabeled trial X

1) Prepossessing the trial signals

2) Apply the pass-band filters to Xz with frequencies F_1' to F_1', F_1'' to F_2'', F_1''' to F_2''',...

3) For each class Compute the covariances matrices.

4) For each unlabeled filtered trial (C′, C″, C″,...) compute the covariances matrices.

5) For each class compute the covariance means (Cz′, Cz″, Cz″,...).

6) Compute the distances (Dz′, Dz″,Dz″e,...) between the covariances matrices C′, C″, C″,... and Riemannian means Cz′, Cz″, Cz″,... respectively, and sum the distances (Dz).

7) Return the class z with minimum distance Dz.

III. Results

We will present the results of three different algorithms : a standard discriminant analysis (LDA), the standart MDM and the MDM with frequential information (MDMfreq). The model validation technique we used is k-fold cross-validation. As a first step, we applied a classification for each participant. Then, we mixed the data from all subjects and did the same validation technique.

The figure 4 shows the average spectrogram of one electrode during hand closing for one subject. As we can see, the spectrum changes as function of frequency and time. The amplitude is maximum for low frequencies (areas where the red color is more intense). We applied different frequency ranges with an exhaustive search to optimize the classification accuracy for each participant. That suggests frequency information in MDM could increase the classification accuracy. Given this, we found five frequency ranges that optimize our algorithm : 25 to 48, 52 to 153, 161 to 229, 266 to 451 and 502 to 720 Hz.

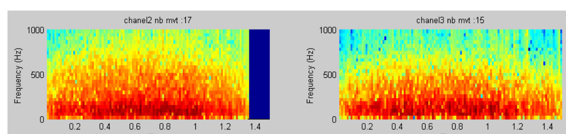

Figure 4: *Spectrogram mean for hand closing motion for one subject and 2 electrodes. When we do the same for different hand motion, we see differences in the spectrograms. That is clue that sEMG contains frequency information.*

We have visualized the covariances matrices positions obtained with two electrodes only on subject 6 (figure 5). We can see that the distribution in the Rimannian space are correlated with labeled data suggesting that the classes are separable from each other.

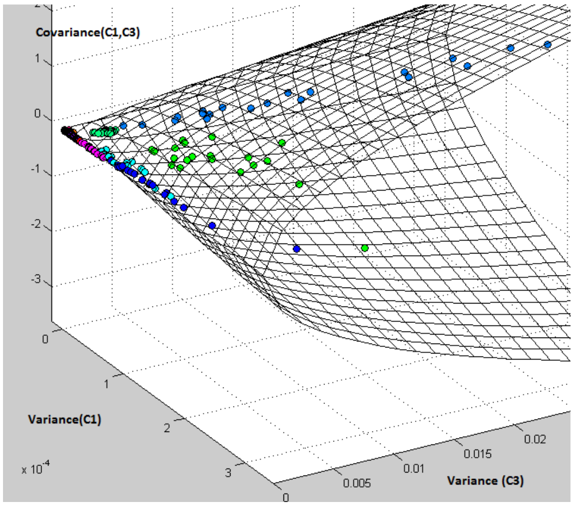

Figure 5: *Distribution of covariances matrices given two electrodes C1 and C3 in the manifold. Each color corresponds to a class.*

The k-fold cross-validation technique separates the data into k equal in size sub-samples. Then, one sub-sample is retained as a validation data and k-1 are retained as training data. In our cross-validation the operation is repeated until all the k sub-samples have been tested as validation data. Then, we compute the confusion matrix with actual and predicted classes and then we compute the classification accuracy.

Figure 6 presents the classification accuracy results of the three algorithms, averaging the results across twenty cross-validation. Performance varies from one subject to another but remains high for all the classification algorithms (>90% except for participants three and four in LDA) and the standard deviations are very low (<0.3) for all participants and methods. Standard LDA shows good classification accuracy with a maximum of 97% for participant three and a mean of 91.91%. The worst result observed is 86,44 % in one session. Standard MDM presents a classification accuracy higher than LDA for five of the six subjects. In comparison to the worst results of LDA, MDM classifies the data with almost 10% better results. With mean accuracy of at 95,97% MDM makes a better classification.

MDMfreq classification accuracy is better than LDA for 5 subject and always as compare to MDM. That confirms our assumption that frequency information could be used in MDM to classify sEMG data. With a mean accuracy of 97,16% MDMfreq method improves the MDM method. Participant three have the best results with 99.77% of classification rate.

	Classification accuracy results (%)		
Subjects	LDA	MDM	MDMfreq
1	95,60	93,36	94,65
2	93,46	94,81	95,37
3	97	99,31	99,77
4	87,07	96,82	98,17
5	86,44	95,32	96,00
6	91,35	96,18	99,02
Mean	91,91	95,97	97,16

Figure 6: *Evaluation of the classification accuracy of the three algorithms for the six subjects separately.*

I. Cross-subejct results

The difficulty in classifying sEMG signal in cross-subject condition is well known. This is ussualy due to the anatomy of the arm and inter variability (arm weight and morphology), cross-talk phenomenon (an electrode can be influenced by the electric activity of a nearby muscle that is not the target muscle), and skin specificity (hair, dead skin, thickness). To resolve these problems, researchers work on the improvement of machine learning and data acquisition (types of electrodes, amplifiers, electrode placement,etc). Our present investigation focus on a machine learning method with naive assumption about electrodes positioning. The figure 7 shows the results of classification in cross-subject condition (data from all participants are mixed and cross-validated). The classification accuracy deteriorates by (which is to be expected) 36% for LDA, 30% for MDM and 27% for MDMfreq. MDMfreq is 14.75% better than LDA and 4.55% than standard MDM. MDMfreq is better significantly better than MDM (p-value<0.001).

	Classification accuracy results (%)		
	LDA	MDM	MDMfreq
All subjects	54,41	64,61	69,16
Standard deviation	0,215	0,314	0,224

Figure 7: *Evaluation of the classification accuracy of the three algorithms for the data from all the subjects (cross-subject).*

When we look in detail the recall and precision of each class (figure 8), we see that the accuracy of MDMfreq is not homogeneous across class. The classes with hand motion (opening the hand, hand flexion and extension, rest) are better recalled except for closing the hand. The worst class recognition is flexion of index. Finger motions are the most difficult to detect in a robotic prosthesis arm. One can also see that the class rest is very high in recall and precision. This a good thing for the future online application because the algorithm will be able to detect no motion activity.

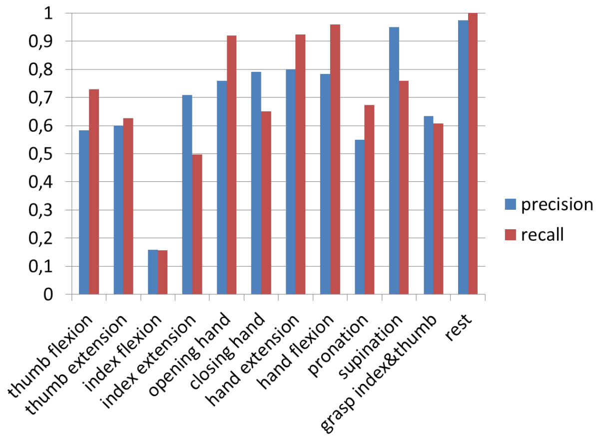

Figure 8: *Evaluation of recall and precision for each motions classified by MDMfreq.*

IV. Discussion

In this paper, we introduce the first attempt to apply Riemannian geometry to classify sEMG signals. The MDM algorithm doesn't require any parameter setting whereas MDMfreq only requires frequency ranges. Riemannian geometric framework is intuitive and simple to adapt with EMG signals. As well-known SVM classifiers are not the best choice for multi-class problems, in contrast MDM algorithms works on cases with multiple classes in a native way. These improvement can be useful to apply them, for example, the field of robotics, in this context efficiently classify EMG signals is needed for controlling robotics arms.

The high classification accuracy reported here shows that the Riemannian distance between covariance matrices provides relevant information to classify, hand and finger motion. An important improvement is obtained when MDM is modified to include frequency information. This shows its adaptation capacity.

However a performance lost is observed when information coming from different participants is used. This may be explained by the fact that there is some inter-variability caused by the anatomical differences between participants. It is also difficult to reproduce in the same way the electrodes placement across sessions. Concerning arm electrodes placement, there is no consensus as it exist for other part of the body (refer for example to SENIAM initiative which is a standards for surface electromyograph). The best method to increase the results is the localization of muscles, but this requires anatomy knowledge. The second step of this study is to investigate the classification accuracy with such methodology. Another explanation of lower performance is the difficulty to concentrate and repeat motions exactly in the same way.

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