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Ageing Effect Evaluation on HD-sEMG signals using CCA approach

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Abstract

Objectives: The objective of the proposed study is to exploit the technology of high-density surface electromyography (HD-sEMG), in order to evaluate the muscle activation in young and elderly subjects during a daily life gesture, namely, Sit To Stand (STS), using wireless connected ambulatory equipment (TMSi[®]) and Blind Source Separation (BSS) approach with Canonical Correlation Analysis (CCA). **Materials and methods:** Sixteen subjects participated (50% females) divided into two categories ('H1': young (30.62 yrs \pm 5.92, 23.95 kg/m² \pm 3.08), versus 'H2': old (61.87 yrs \pm 7.98, 23.4 kg/m² \pm 3.38)), in the recording of HD-sEMG signals, using 32-electrodes square grids (4x8), during Sit To Stand (STS) motion, three times at spontaneous speed. The studied muscle is the Rectus Femoris (RF) muscle. The recorded HD-sEMG signals were analyzed with CCA approach to extract correlation coefficient sets according to two age categories (young versus old), in order to evaluate its discriminating power with ageing. Statistical tests (t-test) were used to evaluate the discrimination for these two categories. **Results:** The calculation of CCA correlation coefficients showed a significant difference between young and old category concerning the mean CCA correlation coefficient ($P < 0.001^{***}$) and also the standard deviation of the CCA correlation coefficients ($P < 0.0001^{****}$). **Conclusion:** The obtained results are promising and indicate a clear difference between the obtained source variability using CCA method between the young and the old tested subjects during daily life motion. Furthermore, these estimated

sources seem to be impacted by both anatomical and functional modifications with ageing.

Keywords: *HD-sEMG technique, CCA algorithm, neuromuscular system, age-related changes, muscle ageing, sarcopenia, wireless medical device.*

1. Introduction

The ageing of the population is a major public health concern, according to World Health Organization (WHO), the proportion of people aged 60 and over will almost double between 2015 and 2025[1]. There are many effects of ageing on the individual, such as the loss of autonomy and the increased risk of falling. This generates important economic, social and psychological costs.

The way of ageing differs from one individual to another. The ageing process is a combination of many factors such as the biological and physiological changes of the organs, the environmental conditions as well as the lifestyle of the person. The consequences of these factors can divide the older population into two categories; the first one with a healthy ageing, and the second one with a pathological ageing characterized by the loss of muscles capacity leading to difficulties in physical tasks during daily life and loss of autonomy.

Sarcopenia, a loss of muscle mass and functionality, is among the consequences of unhealthy ageing. In this context, developing new non-invasive approaches and early evaluation of sarcopenia is a major challenge [2]. Our objective is to develop a wireless medical device based on high-

definition surface electromyography (HD-sEMG) technology, a non-invasive and portable technology, for the diagnosis of muscle ageing. It will allow advances not only for clinical practice in terms of diagnosis to implement appropriate management, but also as a judgment criterion in the screening of therapeutic trials for anti-sarcopenic drugs and nutritional supplements. Other interventions that slow down the effects of muscle ageing with a view for sarcopenia prevention and functional rehabilitation can be monitored using HD-sEMG technique. The scientific issues of this study are twofold: clinical by the evaluation of muscle ageing and methodological through development of a diagnostic tool, compatible with E-health platform, based on the analysis of HD-sEMG signals.

Preliminary study obtained in young and older patients [3] by using the HD-sEMG techniques have shown that HD-sEMG descriptors related to muscular activity are discriminant with the age. In this study, we will record the electrical activity during contraction of RF muscle during Sit To Stand test (STS) using a recent wireless connected and ambulatory portable device and apply the CCA approach, a BSS technique, to analyze the estimated sources and their possible modifications with ageing. The final goal is the remote monitoring of the elderly muscle capacities using a simplified and non-invasive acquisition procedure, which guarantees acceptability by a maximum of patients.

2. Materials and methods

2.1 Experimental protocol

2.1.1 Participants

In this study, sixteen subjects participated in the recording of the experimental signals, divided into two categories (H1 & H2) with the following characteristics:

Category	H1	H2
Gender	4M/4F	4M/4F
Range of age (years)	30.62 ±5.92	61.87 ±7.98
BMI (Kg/m²)	23.95 ±3.08	23.46 ±3.38

Table 1: Cohort description (BMI: Body Mass Index)

All participants provided their written informed consent.

Institutional review boards approved the clinical study (Patient Protection Committee, project number 2018/31). The study was registered on ClinicalTrials.gov ID: NCT03560648. The database was declared to the French National Commission for Data Protection and Liberty (CNIL, France). The subjects presented in Table 1 did not have any history of muscular or neurological disorder.

2.1.2. Experimental setup

Muscle electrical activity during Sit To Stand (STS) motion, 3 times at spontaneous speed, was recorded. The studied muscle is the RF muscle (Figure 1), because it is mainly activated in the STS motion [4]. The positioning of HD-sEMG grids on the muscle is done according to precise standards. Indeed, it is an important source of error; this is why it is important to ensure some repeatability and to follow the European recommendations concerning electrode placement procedures and signal processing methods for surface electromyograms, at the SENIAM project [5]. In fact, the grid was positioned in the proximal region of the rectus femoris (precisely at 30% proximal zone of the rectus femoris (RF) in the iliac spine line located between the iliac crest and the middle of the patella).

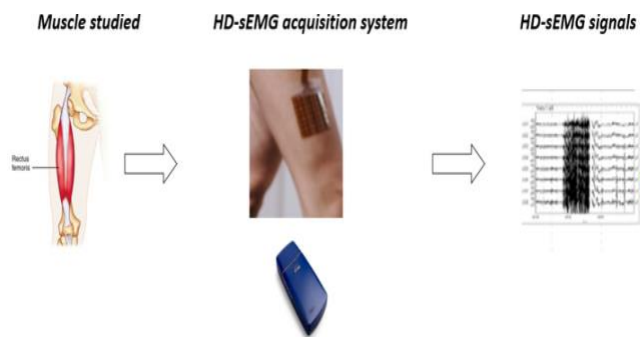


Figure 1: Experimental setup for HD-sEMG signal recording during STS test using Mobita device (TMSi©).

2.1.3 HD-sEMG recording chain

Surface electromyography (sEMG) consists of detecting the electrical activity generated by muscle fibers during a voluntary muscle contraction effort at the skin surface. Surface EMG technique has developed through various events until we arrived at innovative and precise acquisition techniques such as high-density electromyography (HD-sEMG) [6,7]. It

is a non - invasive technique with high precision due to the large number of electrodes in each grid. This makes it possible to analyze the spatial activation during a muscular contraction.

The fundamental principle of electromyography is based on measuring the excitability of the muscle cell. Indeed, the sEMG signal corresponds to the sum of the action potentials (AP) produced by the active motor units and detected on the surface of the skin [8].

The HD-sEMG signals were acquired using MOBITA device: a multi-channel amplifier designed by TMSi[®] (Netherlands), with 32-electrode square grids (4x8) characterized by 4 mm diameter electrodes and an inter-electrodes distance of 8.57 mm. The contact surface from one channel to the other changes and therefore the impedance of the electrodes also changes. However, this difference in impedance can be neglected because of the large input impedance of the device (of the order of 100 MΩ). This contributes to obtain a good signal-to-noise ratio. It is not necessary to perform impedance checking, which facilitates the clinical use of the device.

The system includes the TMSi Polybench[®] processing software for customizing the configuration of the measurement interface. A customized processing software is developed partly by the authors of this study. The sampling frequency is 1000 Hz on a 24-bit resolution. After sampling, the data are transmitted to the laptop/smartphone by Wi-Fi protocol.

2.2 Age effect evaluation using CCA Algorithm

The CCA is a statistical multivariate method that correlates linear relationships between two multidimensional variables. It is used frequently to denoise HD-sEMG signals [9].

The CCA algorithm attempts to extract the original sources, in a BSS paradigm, having maximum autocorrelation values (at a specific time delay) and minimum intercorrelation values with each other [10].

This method has the main advantage of ranking the estimated sources according to a correlation coefficient and allowing the construction of a pertinent thresholding paradigm. It has been successfully used for HD-sEMG signal analysis [9–

11]. It suggests the use of the source vector as the first multidimensional variable and its temporally delayed version as the second[9].

In addition, it proposes to solve the BSS problem by finding the base vectors so that the projections of the variables onto these vectors are mutually maximized[9]. The CCA algorithm attempts to extract the original sources having a maximum autocorrelation value (at a specific time delay) and minimum intercorrelation value with each other.

We assume that a multidimensional random variable:

$$X = [X_1, X_2, \dots X_n] \quad (1)$$

With n being the number of sensors

X is the result of an unknown mixture of unknown source signals:

$$S = [S_1, S_2, \dots S_n] \quad (2)$$

The mixing is assumed to be linear, Therefore, reducing the mixing to a matrix multiplication allows to write [10]:

$$X = A.S \quad (3)$$

Where S, X are respectively the source and the grid signals matrixes of dimension (n×m) with n being the number of sensors and m the number of samples, and A is the mixing matrix of dimension (n×n).

The aim is to retrieve the original source signals S by estimating the mixing matrix A with A is the estimated mixing matrix equal to the inverse of the estimated demixing matrix W. This can be achieved by introducing the demixing matrix W such that:

$$Z = W.X \quad (4)$$

Where the matrix Z approximates the source matrix S by a scaling factor.

Let Y be the delayed version of the source matrix X such that:

$$Y(k) = X(k - 1) \quad (5)$$

Where k represents the sample number.

The one sampling period delay was chosen after multiple denoising trials using different delays between X and Y. The CCA algorithm obtains two

sets of basis vectors, one for X and the other for Y, such that the correlations between the projections of the variables onto these basis vectors are mutually maximized. The mean value of each row from the data matrices X and Y is removed, then by considering: $u = w_x^T \cdot X$ and $v = w_y^T \cdot Y$. The linear combinations of the elements in X and Y, respectively, the correlation between u and v, called the variates or the canonical components, can be represented by [10]:

$$\rho = \frac{E[uv]}{\sqrt{E[u^2]E[v^2]}} = \frac{w_x^T C_{xy} w_y}{\sqrt{(w_x^T C_{xx} w_x)(w_y^T C_{yy} w_y)}} \quad (6)$$

where C_{xx} and C_{yy} represent the autocovariance matrices of X and Y, respectively.

C_{xy} represents the cross-covariance matrix of X and Y, and w_x and w_y are the corresponding weight vectors. Then, the maximization problem will be solved by setting the derivative of ρ , with respect to w_x and w_y , equal to zero which leads to the Eq.

$$\begin{cases} C_{xx}^{-1} C_{xy} C_{yy} w_x = \rho^2 w_x \\ C_{yy}^{-1} C_{yx} C_{xx} w_y = \rho^2 w_y \end{cases} \quad (7)$$

With ρ is the square root of the eigenvalue, w_x and w_y are Eigen vectors of $C_{xx}^{-1} C_{xy} C_{yy}$ and $C_{yy}^{-1} C_{yx} C_{xx}$, respectively.

The first variates obtained by CCA are, thus, maximally correlated with each other [9]. The next pair of weight vectors is obtained likewise by finding variates, which are maximally correlated with each other and uncorrelated with the variates of the first pair.

All the variates are found in an iterative manner [9,11]. Consequently, these variates are considered as the sources having maximal autocorrelation and are uncorrelated with each other. Thus, when CCA algorithm is applied on the raw HD-sEMG signals matrix, we obtain the sources (estimated canonical components) ranked from the higher to the lower delayed autocorrelation. The algorithm therefore extracts the original sources of the signal having a maximum autocorrelation value and a minimum inter-correlation value between them [9].

The advantage of this separation is that the sources are sorted according to their correlation coefficient

value. Thus, the first source will have the highest autocorrelation approximately equal to 1 and the last source will have the lowest autocorrelation close to 0. We propose to evaluate the obtained correlation coefficient set according to two age categories (young versus old) to evaluate its discriminating power. For each participant in each category (H1 and H2), we computed the averaged correlation coefficients of 31 sources (the channel 32 is the reference) (Figure 2) and the standard deviation (std) of these sources, then we compute the average of this two parameters (mean and std) in each category. Finally, we compare the data of young and old category by using statistical tests (t-test) to evaluate the discrimination for these two categories.

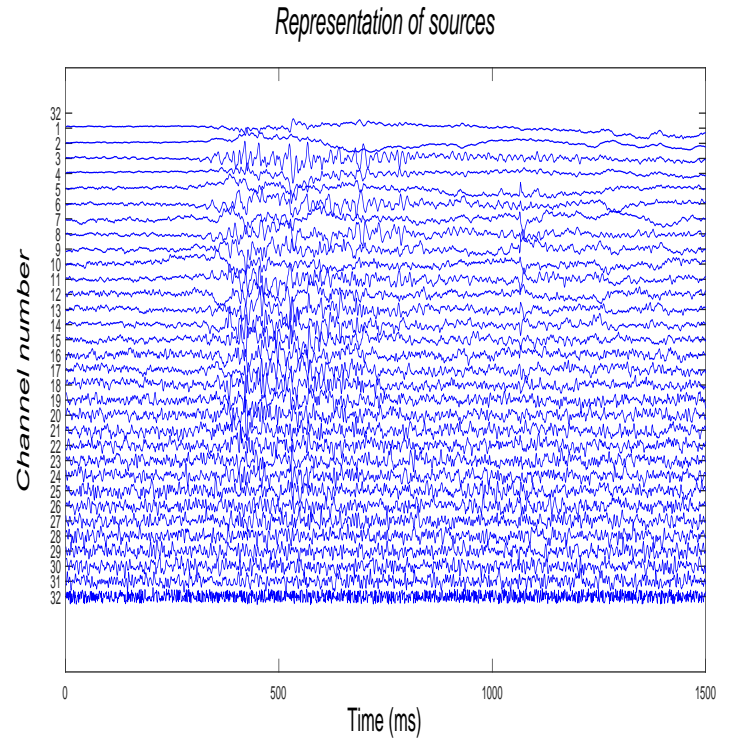


Figure 2: Representation of canonical components (estimated sources) for one subject during STS motion.

3. Results and Discussions

The calculation of CCA correlation coefficients showed a significant difference between young and old category concerning the mean CCA correlation coefficient ($P < 0.001^{***}$) and also the standard

deviation of the CCA correlation coefficients ($P < 0.0001^{****}$) as exposed in Table 2.

	H1	H2	t-test
	(young)	(elderly)	(P-value)
SNR (dB)	18.13 ±4.59	18.12 ±4.86	
Mean Correlation coefficient	0.86±0.07	0.90 ±0.08	$P < 0.001^{***}$
Std of correlation coefficient	0.16±0.04	0.091± 0.06	$P < 0.0001^{****}$

Table 2: t-test results for H1 and H2 groups

A higher correlation coefficient observed in the older group can be related directly to spectral content of the muscle electrical activity; because of the SNR goodness, we assume that these modifications in the correlation of sources can be related to muscle activity changes with ageing and generating differences with the young category.

Indeed, we explain this higher autocorrelation values in old population by the presence of more sources with narrower spectral bands (related to larger autocorrelation functions) in contrary to the young category. This should be linked to the modifications of muscle fibers typology; Elderly people have more MUs of type I (slow velocity) and less type II (fast velocity) compared to young people [12]. Type I fibers are characterized by a low force, power and speed production but an important endurance. These fibers have slow contraction and a slow fatigability. They are used in low force level requiring activities like walking, posture maintaining and in daily activities such as STS motion used in the present study.

The motor units that contains these types of fibers are called slow motor units [6,8]. That is why the muscle fibers Type I are more dominant with ageing. In contrary Type II fibers are described by having a high force production but low resistance to fatigue and bigger diameter than the type I fibers [6,8]. Type II MU electrical activity exhibits larger spectral content and narrower autocorrelation function. They are present in the young category. This could also explain the rapid decay of the CCA

correlation coefficient trend in young category (H1) compared to the old category (H2) as depicted in Figure 3.

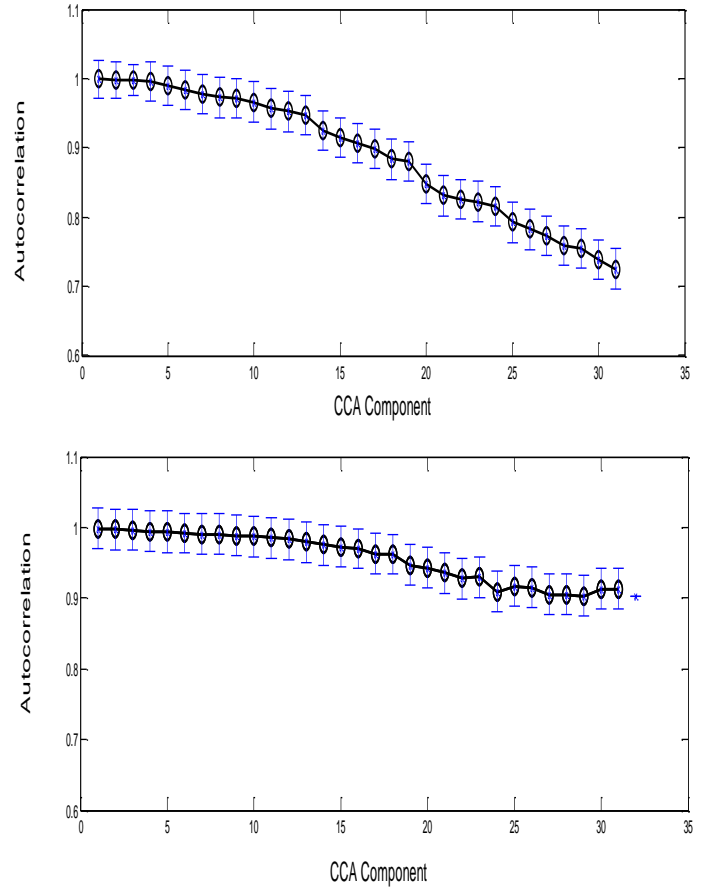


Figure 3: Obtained CCA correlation coefficients for the 31 estimated sources for young (H1) “up” and elderly (H2) “down” groups.

In fact, this figure shows the trends of the average correlation coefficients, for each source and each age category; this result is complementary with the t-test and validate the utility of CCA approach not only in the aim of signal denoising but also in order to extract new features sensitive to muscle changes with ageing. This will be exploited in future work, combined to classification approaches, to better separate age categories. In addition, these autocorrelation trends will be also investigated using middle-age category in a next study.

The study of Watanabe et al. on the relationships between muscle strength and multi-channel surface EMG parameters in eighty-eight elderly shows also a high correlation of HD-sEMG parameters in the elderly subjects [13]. This high correlation is supposed to be linked to the modulation of muscle

structure with ageing and not only to the atrophy. This result agrees with our study and notably with the result of Figure 4, which also shows clear modifications with ageing. These modifications can be functionally evaluated by HD-sEMG parameters such as correlation coefficient from CCA proposed in the present study.

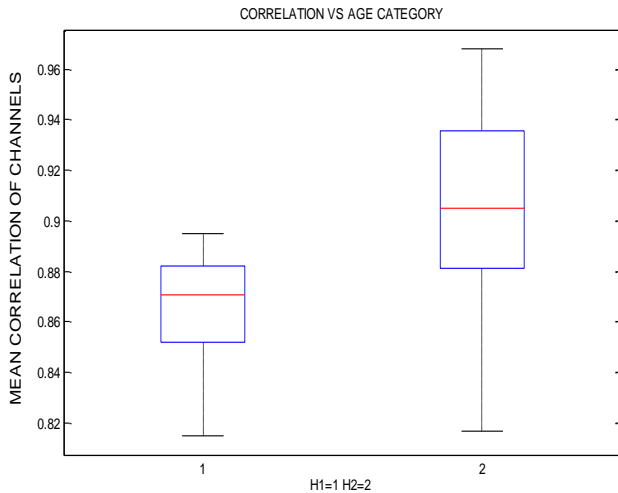


Figure 4: Boxplot of the mean correlation coefficient of the estimated sources for H1 (young) and H2 (elderly) groups.

We observed also that the standard deviation of the autocorrelation coefficient (Figure 5) significantly decreases in old category compared to young category. This can be also related to the variation in muscle architecture and thickness which are modified with ageing and can be assessed using ultrasonography imaging [14]. Note also that the standard deviation disperses even more in the elderly than in the young. This is possibly due to the heterogeneity of the muscular structure and electrical activity that seems to increase with ageing, among subjects, as shown in a recent study [15]. It is important to note that the BMI index is similar in both age categories (Table 1) to avoid signal filtering effects due to the adipose tissue that could bias the result interpretation.

The present study aims at exploiting the advantages of combining the HD-sEMG technique and CCA approach, using autocorrelation coefficients (mean and standard deviation of the sources) and statistical test (t-test) to evaluate ageing

effect throughout life using classification of CCA sources.

We observed a trend of sources that clearly differentiates each category (young and old). This could be related to anatomical and functional modifications related to ageing and not solely to the atrophy process [13]. However, gender difference analysis has not been addressed in this study in order to keep the power of the statistical testing according to the small database size. The database will be increased in size with further clinical studies assessing gender differences.

The main aim of this study is to give objective and intuitive information, using few parameters, to the clinician related to muscle decline and to contribute in finding solutions for standardization of ageing effect evaluation as previously mentioned [2].

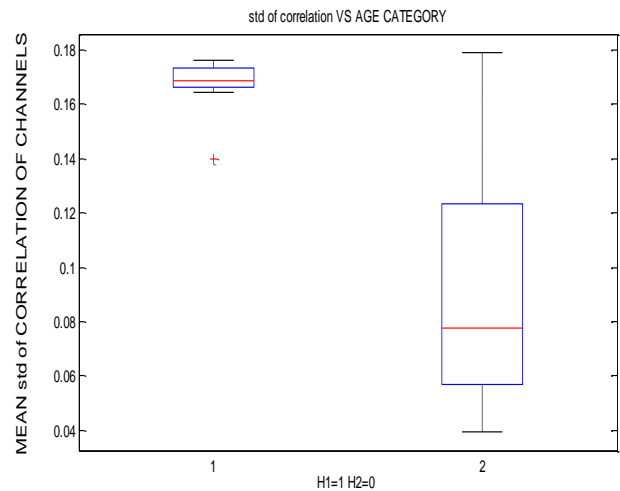


Figure 5: Boxplot of standard deviation of CCA correlation coefficients for the estimated sources for H1 (young) and H2 (elderly) groups.

Further studies are needed to better explain the complex mechanisms underlying muscle ageing. This study is relevant to introduce new parameters from HD-sEMG signal processing, in order to demonstrate some differences in muscle activity linked to age-related changes in clinical routine. To make easier the implementation of this study in clinical applications, the information chain from clinical investigators to engineers and analysts was already successfully tested in clinical environment during the data acquisition process. Indeed, thanks to the data

management tools set up in the clinical environment and in the research laboratory, the data communication is practical. The frequency of the measurements will depend on the needs of the clinicians for patients' follow-up.

4. Conclusion and perspectives

The obtained results are promising and indicate a clear difference between the obtained source variability using CCA method between the young and the old tested subjects during daily life motion. This study allowed us to unveil the potential of the CCA approach in a deeper screening of muscular modifications with ageing, starting from the idea to support therapeutic and prevention approach of sarcopenia in the elderly. The results indicated clear modifications in the electrical activity, measured by HD-sEMG technique, related to muscle activity during STS motion. These modifications should be linked to both anatomical and/or functional changes and be better investigated in future works.

Finally, through this study, the HD-sEMG ambulatory used device demonstrated its usefulness in rapid and wireless evaluation of muscle capacities, opening the door for clinical applications related to E-Health and personalized medicine. Expected benefits are not only for the elderly, but also for the young, to alert them about future dangers related to ageing as sarcopenia. Thus, physiotherapists and clinicians could routinely employ the proposed device for muscle assessment through life.

Conflict of interest statement

No conflict of interest

Acknowledgment

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Materials and methods

Category	H1	H2
Gender	4M/4F	4M/4F
Range of age (years)	30.62 ±5.92	61.87 ±7.98
BMI (Kg/m ²)	23.95 ±3.08	23.46 ±3.38

Table 1: Cohort description (BMI: Body Mass Index)

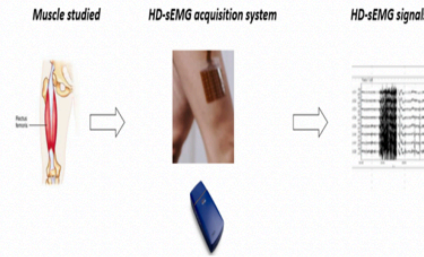


Figure 1: Experimental setup for HD-sEMG signal recording during STS test using Mobita device (TMSi©).

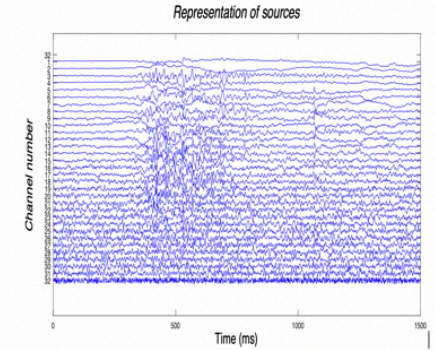


Figure 2: Representation of canonical components (estimated sources) for one subject during STS motion.

Results

	H1 (Young)	H2 (Elderly)	t-test (P-value)
SNR (dB)	18.13 ±4.59	18.12 ±4.86	
Mean Correlation coefficient	0.86±0.07	0.90 ±0.08	$P < 0.001$ ***
Std of correlation coefficient	0.16±0.04	0.091± 0.06	$P < 0.0001$ *** *

Table 2: t-test results for H1 and H2 groups

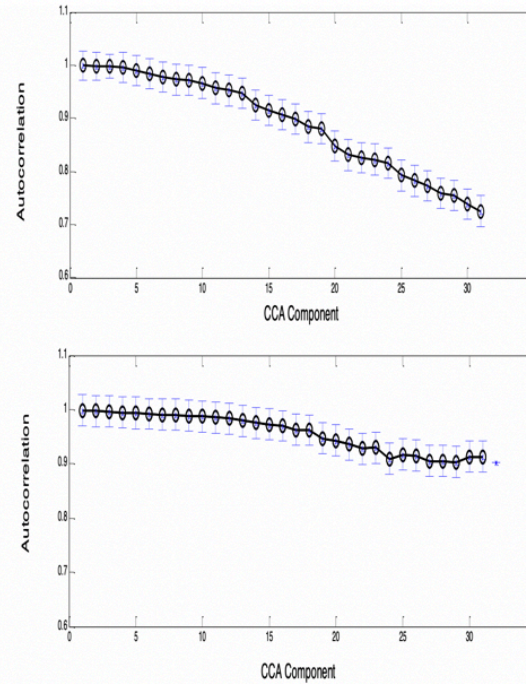


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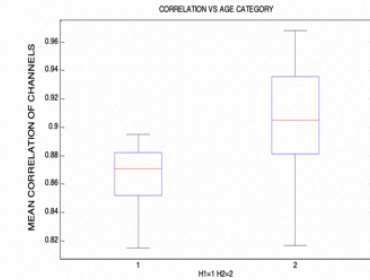


Figure 4: Boxplot of the mean correlation coefficient of the estimated sources for H1 (young) and H2 (elderly) groups.

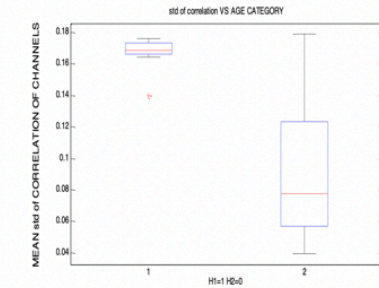


Figure 5: Boxplot of standard deviation of CCA correlation coefficients for the estimated sources for H1 (young) and H2 (elderly) groups.