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Computerized classification of corpus cavernosum electromyogram signals by the use of discriminant analysis and artificial neural networks to support diagnosis of erectile dysfunction

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Abstract Corpus cavernosum electromyogram (CC-EMG) provides diagnostic information on cavernous autonomic innervation and a measure of the degree to which the cavernous smooth muscle cells are intact. The complicated CC-EMG is evaluated and used in the diagnosis of patients suffering from erectile dysfunction. The evaluation procedure has been simplified by applying digital signal processing techniques. Since mathematically-based interpretations require quantitative data, spectral analysis was performed. The derived biosignals were analyzed by fast Fourier transform (FFT). Besides various other spectral parameters, specific frequency bands were determined in the power spectrum using factor analysis. The parameters were used for the computerized classification of normal and pathological CC-EMG data and the classification was performed using two independent methods: discriminant analysis (DA) and artificial neural networks (ANN). A medical expert analyzed a total of 200 CC-EMG recordings from patients with and without erectile dysfunction and separated these into normal (136) and pathological (64) cases. Although each independent method had already resulted in a relatively high number of correct classifications, the classification success rate could be slightly improved by using a combination of both classification methods. A total of 72.79% and 77.94% were successfully classified using DA and ANN, respectively. The combination of both methods increased the classification success to 80.15%. The results of this study enabled impartial evaluation of the CC-EMG signals for clinical diagnostic purposes of erectile dysfunction. This method provided an objective and easy way to analyze the CC-EMG. Furthermore, this results in patient diagnosis becoming an easier task for less experienced doctors, since little knowledge of the raw signal is needed.

Key words Erectile dysfunction · Corpus cavernosum electromyogram · Biosignal classification · Discriminant analysis · Artificial neural networks · Fast Fourier transform

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Corpus cavernosum electromyogram (CC-EMG) has recently attracted scientific attention since it may provide information about cavernous autonomic innervation and cavernous smooth muscle cell intactness [11, 12, 23, 24, 26, 29, 30]. Meanwhile, the CC-EMG has been part of a comprehensive diagnostic process to determine the cause of erectile dysfunction [4, 25, 30] since 1988, when electrical activity of the corpus cavernosum was discovered [30]. CC-EMG has become a routine diagnostic method in leading centers worldwide [15, 16, 19, 20, 27]. However, the interpretation of the derived biosignals is still complex. Recording of the CC-EMG is analogous to the recording of EMGs of other smooth muscle cells like the urinary bladder [3, 14, 17]. However, diagnosis is difficult due to the complexity of the biosignals and the required experience of the examiner. Another problem is the long duration of a recording session which normally lasts approximately 1 h.

We therefore attempted to simplify the method by the application of computer-based digital signal processing algorithms. Simplification, time reduction and an increased level of objectivity during the assessment procedure were the main goals of this work.

Material and methods

The characteristic activity patterns of the CC-EMG signals constituted the input data for all research activities in this work and have already been investigated and published [5, 6, 23, 24, 29]. Figure 1 depicts two typical raw CC-EMG signal patterns.

Data acquisition of the CC-EMG signals was performed as described in [9, 13]. As shown in Fig. 2, the artifacts were interactively eliminated directly after digitization [13] (before any further signal processing was performed).

Isoelectric segments have been filtered from the recording, and only the clinically significant potentials remain in the complete recording because they contain the important information about the patients' state of disease. The extracted epochs were subsequently transformed from the time domain (spontaneous electrical activity over time) to the frequency domain (signal amplitude over frequency) by the use of fast Fourier transformation (FFT). In detail, for each pattern segment, L, the periodogram, Per_L, was calculated. Then all periodograms of one recording were averaged and the power density spectrum was calculated. An overview of the data preprocessing is shown in Fig. 3.

Typical CC-EMG patterns of power density spectra have already been published [9, 13, 26, 28] as illustrated in Fig. 4. There is a characteristic difference in power density distribution for people who suffer from erectile dysfunction and those who do not. Previous studies [9, 13, 25, 28, 29] have shown that the essential bandwidth of CC-EMG spectra is 0–10 Hz, and our own calculations confirmed that an average of 95% of the spectral power is located below 1.5 Hz. Although some power density is around 10 Hz, it can be disregarded for the evaluation of the spectra in this case. Power density spectra of pathological and normal groups of patients can be clearly distinguished by visual inspection of the power distribution within the range of 0–10 Hz.

Specific essential parameters characterizing the CC-EMG spectra can be determined similar to those used in the field of processed electroencephalography (EEG) [10]. The spectral parameters may directly correlate with the patient's state of disease, and lead to a reduction in data, thereby simplifying the interpretation of the recorded measurements. For computer-based classification of CC-EMG data recordings, the spectral parameters can be used effectively as initial input values.

All calculations are based on identical data sets and a total of 100 previously recorded CC-EMGs were used. The database consisted of 68 recordings from patients with erectile dysfunction of different etiologies and 32 recordings from normal men (without erectile dysfunction). All recordings were classified into two groups (N, normal; P, pathological) by an expert. Because all CC-EMGs were recorded simultaneously with two channels (left and right corpus cavernosum), a total of 200 spectra (64 normal, 136 pathological) constituted the basis for all further analysis. The set of 200 spectra was split into two independent subsets. One data set served as a training set and the other one was used to validate the classification method (test set). Details about the composition of each set are shown in Table 1.

All CC-EMG signals were recorded with a neurophysiological unit (DANTEC Neuromatic 2000 M, Dantec, Copenhagen, Denmark) and the bandwidth used was located between 0.5–100 Hz. Using amplification and anti-aliasing low pass filtering with a cut-off frequency at 64 Hz in the hardware, the signals were digitized with 12-bit resolution. All data were sampled at a frequency of 170.6 Hz and stored in binary format. The CC-EMG potential patterns were extracted by a software algorithm using both gradient and threshold value methods; artifacts were interactively eliminated as shown in Fig. 2. The remaining potentials were weighted with a parabolic spectral window and then transformed into the frequency domain using an FFT method (Bartlett method) as depicted in Fig. 3. Each segment had a length of 2048 samples resulting in a frequency resolution of 0.0833 Hz [13].

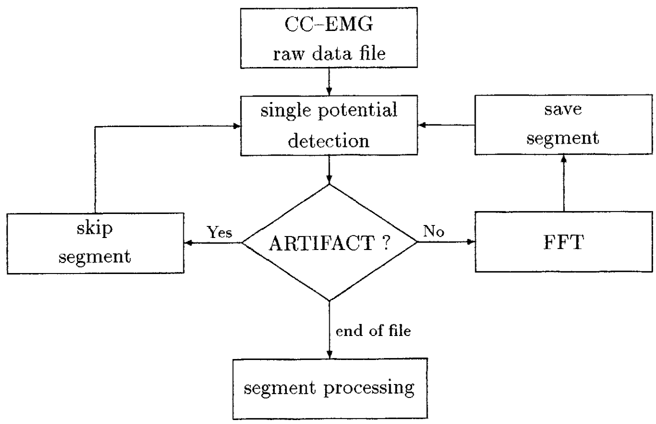


Fig. 2 Block diagram of the user interactive artifact elimination process

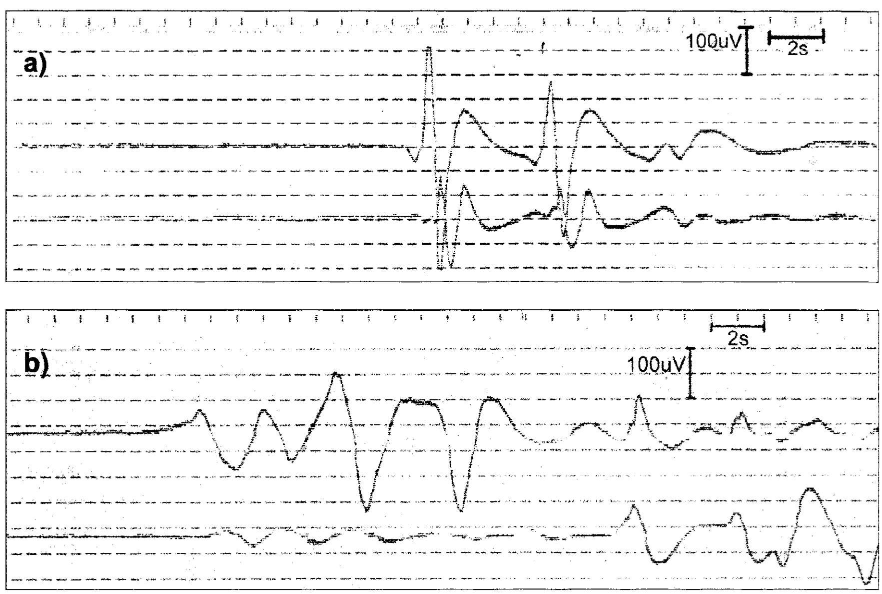


Fig. 1a, b Typical signal patterns of a computerized classification of corpus cavernosum electromyogram (CC-EMG) recording taken from (**a**) a normal person and (**b**) a 56-year-old patient suffering from diabetes mellitus and erectile dysfunction

Fig. 3 Spectral analysis of CC-EMG data: transformation of CC-EMG signal patterns from the time domain into the frequency domain

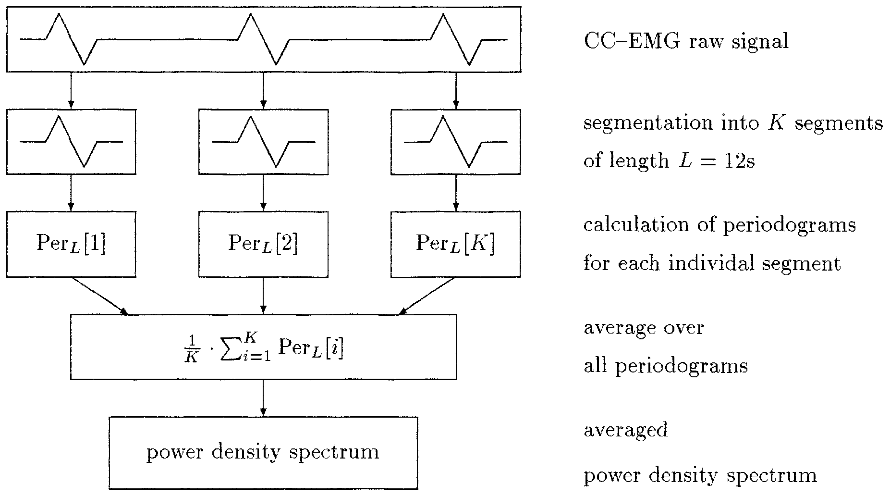
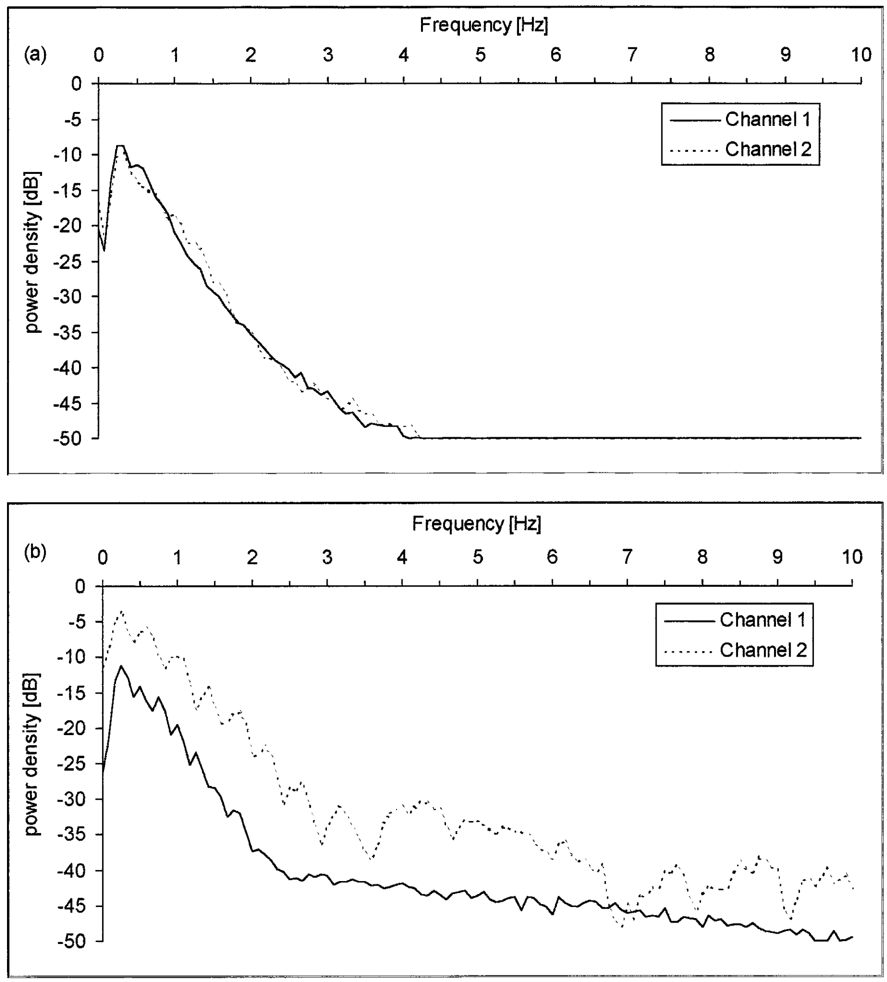


Fig. 4a, b Typical patterns of power density spectra taken from (**a**) a person without erectile dysfunction and (**b**) from a patient with erectile dysfunction after pelvic ring fracture



After subdividing the spectrum into a set of four consecutive frequency bands, a set of 16 descriptive spectral parameters was defined for each CC-EMG spectrum. Besides parameters like amplitude and spectral edge frequencies, mean values for each particular frequency band were calculated. To determine specific frequency bands in the CC-EMG power density spectra, factor analysis was applied as a statistical method [13]. Absolute and relative band power and ratios of these parameters were also calculated. The parameters calculated for each recording are shown in Table 2.

Figure 5 explains some of the parameters by means of a discrete sample power spectrum. The frequency band power limits are displayed as published in [13] (δ, 0.0–0.3 Hz; θ, 0.3–3.5 Hz; α, 3.5–6.0 Hz; β, 6.0–10.0 Hz).

Table 1 Composition of class N (i.e. classified as "normal" by the physician) and P (i.e. classified as "pathological" by the physician) recordings for the calibration and verification data set

	Calibration data set	Verification data set
Number of class N recordings	38	96
Number of class P recordings	26	40
Total number of recordings	64	136

Table 2 Spectral parameters calculated and derived from the fast Fourier transformed CC-EMG signals

No.	Designation	Symbol
1	Maximum amplitude	A_{max}
2	Total power	P_{tot}
3	Absolute band power	δ_{abs}
4	Absolute band power	θ_{abs}
5	Absolute band power	α_{abs}
6	Absolute band power	β_{abs}
7	Power ratio q_1	θ_{abs}/β_{abs}
8	Power ratio q_2	$(\theta_{abs} + \alpha_{abs})/\beta_{abs}$
9	Relative band power	δ_{rel}
10	Relative band power	θ_{rel}
11	Relative band power	α_{rel}
12	Relative band power	β_{rel}
13	Mean amplitude	A_{mean}
14	Spectral median frequency	SMF
15	Spectral edge frequency 90%	SEF_{90}
16	Spectral edge frequency 95%	SEF_{95}

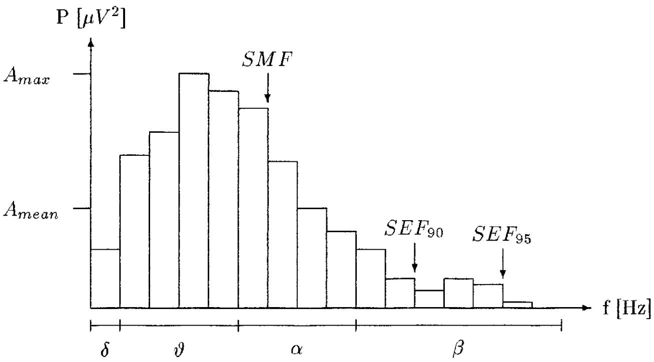


Fig. 5 Some spectral parameters (see also Table 2). A_{mean}, average spectral power; A, largest spectral power value; δ, α, β, spectral power bands; *SMF*, 50% of total power; SEF_{xx}, xx% of total power

The individual parameters contain different information and a different amount of discriminant power. The parameters constituted the input vector for both classification methods.

Discriminant analysis

This was utilized as a linear statistical classification method. Discriminant analysis determines a linear combination of dependent variables of a spot-check. This enables a maximum degree of distinction between the compared classes by the use of specific class characteristics. Initially, stepwise discriminant analysis was applied to achieve an effective discriminant model. The variables with the highest degree of discriminating power have been selected from the parameter set in this calculation step. The computerized recommendation of parameter combinations was then used for a complete discriminant analysis. To achieve better results, various other spectral parameters were added to and removed from the mathematical model and appropriate analysis was performed. Due to the time consuming nature of the trials (using different parameter combinations), the optimization process was abandoned when high classification success rates were achieved.

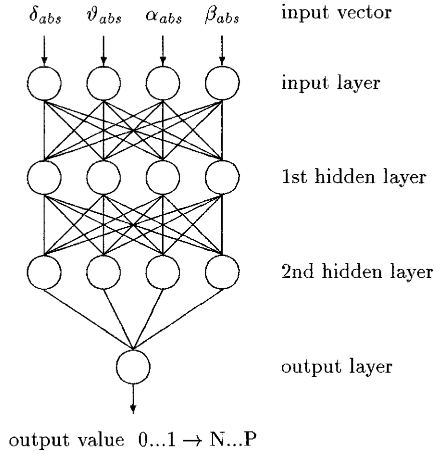


Fig. 6 Network layout of the artificial neural network classificator

Artificial neural networks

These were used as a second classification method. The idea and mathematical theory behind artificial neural networks (ANN) are described elsewhere [32]. A variety of networks and learning algorithms are available, including the most often used feed-forward ANN, which is well known for classification and pattern recognition applications. Among others, an artificial neural network with two hidden layers and Backpropogation-Momentum [32] was used as a learning method shown in Fig. 6.

The network topologies were also modified. Simpler topologies achieved approximately the same results as the two hidden layer types. Networks with a more complex topology did not provide better results, but the showed a significant increase in calculation time.

In order to continue with the ANN, parameters such as learning method and the corresponding configuration, calculation steps, number of input parameters, standardization of input parameters or the network topology were applied systematically with the aim of achieving the best classification results.

The classification results of both methods are based on the same data sets that were used for calibration and verification purposes. This provides an objective way of comparing the performance of each classification method. The reference class of each recording, given by an expert, was compared with the computer-based classification method results. The success rate of the classification is determined by the ratio of correctly classified recordings of the verification set to the total number of recordings in that set as shown in Eq. (1).

$$\text{classification success rate} = \frac{\text{number of correct classifications}}{\text{total number of classifications}} \qquad (1)$$

Due to the large number of parameters in both classification methods, it was evident that computer-based methods must be applied. Therefore, all calculations regarding discriminant analysis were performed with the SAS statistic software [21, 22] and all ANN calculations were performed with the Stuttgarter Neuronale Netze Simulator (SNNS) [32].

Results

The preselection of the most powerful parameters by stepwise discriminant analysis lead to three out of 16 calculated parameters (β_{rel}, SMF, α_{abs}). Discriminant analysis with these parameters achieved a total classification success rate of 61.8%. After interactively modifying the parameter selection as described before, a total classification success rate of 72.79% was achieved. Details are given in Table 3.

The best results were be achieved when six spectral parameters (β_{rel}, θ_{abs}, θ_{rel}, δ_{abs}, SEF_{90}, SEF_{95}), found by iterative selection, were used. The coefficients for the linear discriminant function are as follows:

$$D_N = -18.75 - 154.92 \cdot \beta_{rel} - 127.24 \cdot \theta_{abs} + 49.02 \cdot \theta_{rel} + 347.07 \cdot \delta_{abs} - 2.27 \cdot SEF_{90} + 4.92 \cdot SEF_{95} \quad (2)$$

The value D_N describes the posterior probability of membership in class N (normal signal) of any CC-EMG observation. Values equal to or greater than 0.5 indicate a normal CC-EMG, while lower values indicate pathological data. The appropriate value for class P (pathological signal) can be calculated easily by:

$$D_N = -18.75 - 154.92 \cdot \beta_{rel} - 127.24 \cdot \theta_{abs} + 49.02 \cdot \theta_{rel} + 347.07 \cdot \delta_{abs} - 2.27 \cdot SEF_{90} + 4.92 \cdot SEF_{95} \quad (3)$$

Using Eq. (2), the classification of any CC-EMG recording is possible in the frequency domain, provided the signal processing method previously described is used.

Various calculations with different compositions of ANN as a second classification method have been performed. Due to the lack of mathematically based optimization methods, the suitability and performance of an appropriate network or learning method and the corresponding combination of parameters was iteratively analyzed. The best results in this study were achieved with a hidden two-layer ANN with Backpropagation-Momentum as the learning method [32]. The input vector for ANN contains only four parameters with the absolute power in each of the four frequency bands determined by factor analysis in a previous study [13]. Detailed results of the most successful analysis with ANN are shown in Table 4.

The network configuration and additional information about the learning algorithm is provided in Table 5. The topology of the network (i.e. one input and output layer and two hidden layers) is identical to that shown in Fig. 6.

All results for ANN and DA classifications are based on the test data set. This means, that these data have not been classified by one of the classification methods before and are therefore as meaningful as any other new recording made during daily clinical use of CC-EMG.

The final classification success rate of 77.94% when ANN was applied is superior to that with discriminant analysis. Note that the classification results for normal (84.38%) and pathological data (62.5%) are given separately. The results were obtained with a normalized input vector and an early stopping method [ ]. Equation (4) was evaluated in order to normalize the data for each input vector component and used for the classification.

$$x_{normalized} = \ln\left(\sqrt{x}\right) \quad (4)$$

Other learning methods such as Quickprop, Rprop or simple Vanilla Backpropagation [32] were utilized and different combinations of their corresponding parameter sets tested. However, none of the results could surpass the Backpropagation-Momentum method used in this study. Further modifications of the input vector, weight initialization, pattern presentation mode or learning steps did not influence the results in a considerable way.

Attempts to achieve better results by using the input data of ANN investigations for discriminant analysis and vice versa did not improve classification results. The intention of this cross-checking was to compare the results of the classification methods for input data combinations used for the respective methods. In this study it was not possible to improve the results with modifications to the input data or configuration.

Comparing the results from both classification methods, discriminant analysis is better suited for the detection of pathological data than ANN, while ANN was superior for normal data. This effect could also be seen when the classification results were directly compared with each other. To develop a combined classification method of discriminant analysis and ANN with better performance, each classification result from both

Table 3 Classification results of the most successful discriminant analysis

	Class N	Class P	Total
Correct	68	31	99
False	28	9	37
Classification rate	70.83%	77.5%	72.79%

Table 4 Classification results of the most successful calculation with an artificial neural network

	Class N	Class P	Total
Correct	81	25	106
False	15	15	30
Classification rate	84.38%	62.5%	77.94%

Table 5 Parameters and configuration of the applied artificial neural network with Backpropagation-Momentum term

Parameter	Value
Learning mode type	Sequential
Accidental weight initialization range	[−1.0;1.0]
Weight update order method	Topological
Learning rate ηh	0.2
Momentum term μm	0.3
Flat spot elimination c	0.05
Maximum tolerance difference d_{max}	0.1
Training steps	35

classification methods was evaluated with regards to the distance from the class threshold value. Figure 7 shows the improved performance of the combined classification method. To classify each CC-EMG with the combined classification method, the respective set of spectral parameters must be calculated.

The data set is classified by discriminant analysis first. For normal data, the process is complete at this point. If the data is not normal, the data set is classified by the ANN again, which provides the final classification result. Table 6 shows the results obtained by using this combined method.

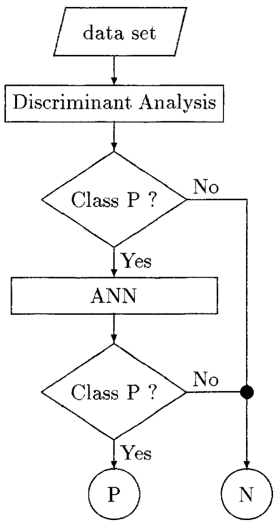


Fig. 7 Block diagram of the combined classification method of discriminant analysis and artificial neural network

Table 6 Classification results of the combined classification

	Class N	Class P	Total
Correct	85	24	109
False	11	16	27
Classification rate	88.54%	60%	80.15%

Finally an improved total classification rate of 80.15% was achieved. Normal data was recognized with a rate of 88.54% and pathological data with 60%. In Fig. 8, classification results of all three methods are compared and summarized.

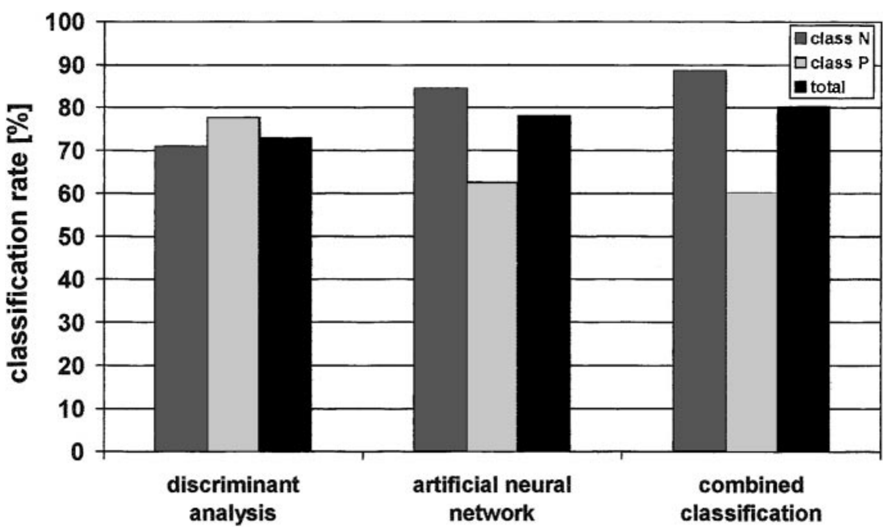
The developed combination is one out of several possibilities for combining both methods. In this study the classification rate for normal data could be improved at the expense of those for the pathological data. Other combinations might have achieved even better results, but no method of analysis could be found to optimize the performance further. Because CC-EMG is part of a comprehensive diagnostic process for detecting erectile dysfunction, the probability of a general false positive diagnosis is small, particularly if the relatively high classification success rate for normal data is considered. Other parts of the complete diagnostic process [25] will prevent general false-positive diagnostic decisions, since the choice of therapy is never based on a single result from one diagnostic method and a physician's attention is not focused solely on CC-EMG.

Discussion

All analysis and calculations were based on 200 spectral analyzed CC-EMG recordings. The database was split into two independent data sets, which were used for calibration ($n = 64$) and verification (test classification) purposes ($n = 136$). This large amount of data was acquired from routine diagnostics performed daily. Therefore, we conclude that to some extent these results may be interpreted as a generalized outcome. Nevertheless, a clinical validation with a completely independent set of data is currently pending.

Both discriminant analysis and ANN, achieved promising classification results. Discriminant analysis enabled a classification success rate of 71.88%, while for

Fig. 8 Comparison of the classification success rates for all three classification methods



results from using ANN this was 77.94%, based on the verification data set. Discriminant analysis resulted in a higher classification success rate for normal CC-EMG recording, while ANN was more successful at identifying pathological data. It is possible that further trials and modifications might lead to even better classification success rates than those calculated, but the described combination of both methods already provides a high rate of 80.15%. Based on physiological data and its known variations, it is remarkable that the computerized classification methods provide reliable results while using only four spectral parameters in the case of the ANN classification method or six in the case of discriminant analysis. One benefit of the spectral parameters is their simplicity compared to the complex time domain parameters. Finally, the signal processing and classification in the frequency domain enables further use of the CC-EMG for a wider range of users.

The calibration and verification data sets were given the same reference class for left and right channel by a medical expert. In the classification analysis both channels were considered independent. A difference in classification results between the two channels was observed for the verification data set. With discriminant analysis, both channels were wrongly classified in six cases and furthermore a deviation between the left and right channel was found in 25 cases. Based on the 136 recordings in the verification set, this represents a rate of 4.41% and 18.38%, respectively. Nearly the same results were obtained for classifications with ANN, where five (3.68%) recordings were wrongly classified in both channels and 20 (14.71%) showed deviations between left and right channels. The reason for the different classification has not yet been determined, but it may be caused by individual variations in the recordings. Therefore, the reference class should be given separately for further examinations. Also, the classification method may be improved for cases very close to the threshold value of the class limits.

Discriminant analysis, artificial neural networks and the specific combination of both methods achieved reproducible and successful classification results. Nevertheless, the computerized classification still needs some fine-tuning for robust clinical use. Classification methods other than those already developed are conceivable, which may lead to improved results. Fuzzy logic has already been applied to evaluation of CC-EMG data [7]. This has achieved classification success rates of 70%, but was only based on 30 recordings. Different ANN types have been successfully applied in the analysis of sleep EEG data [1] and various other fields of medical applications like carcinogenicity prediction [2] or different urological diseases [31] where other methods were also successful. In particular, consideration of the significant signal characteristics in the time domain combined with spectral analysis could improve the separation process. Reliability and efficiency of the computer-assisted diagnosis could be improved by automated artifact detection and elimination, which is currently limited by the user's experience. Furthermore, exception handling must be implemented for special cases and the diagnostic importance of the frequency range below 0.5 Hz also needs clarification.

By using the computer-based CC-EMG evaluation and classification, the doctor is supported in his diagnostic decision by an objective, time-saving and easy-to-use method without the need for a deep knowledge of the complex raw signal. Even new users of this method and perhaps those assisting clinical staff, are able to use the CC-EMG to obtain information about a patient's cavernous autonomic innervation and the intact state of cavernous smooth muscle cells.

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