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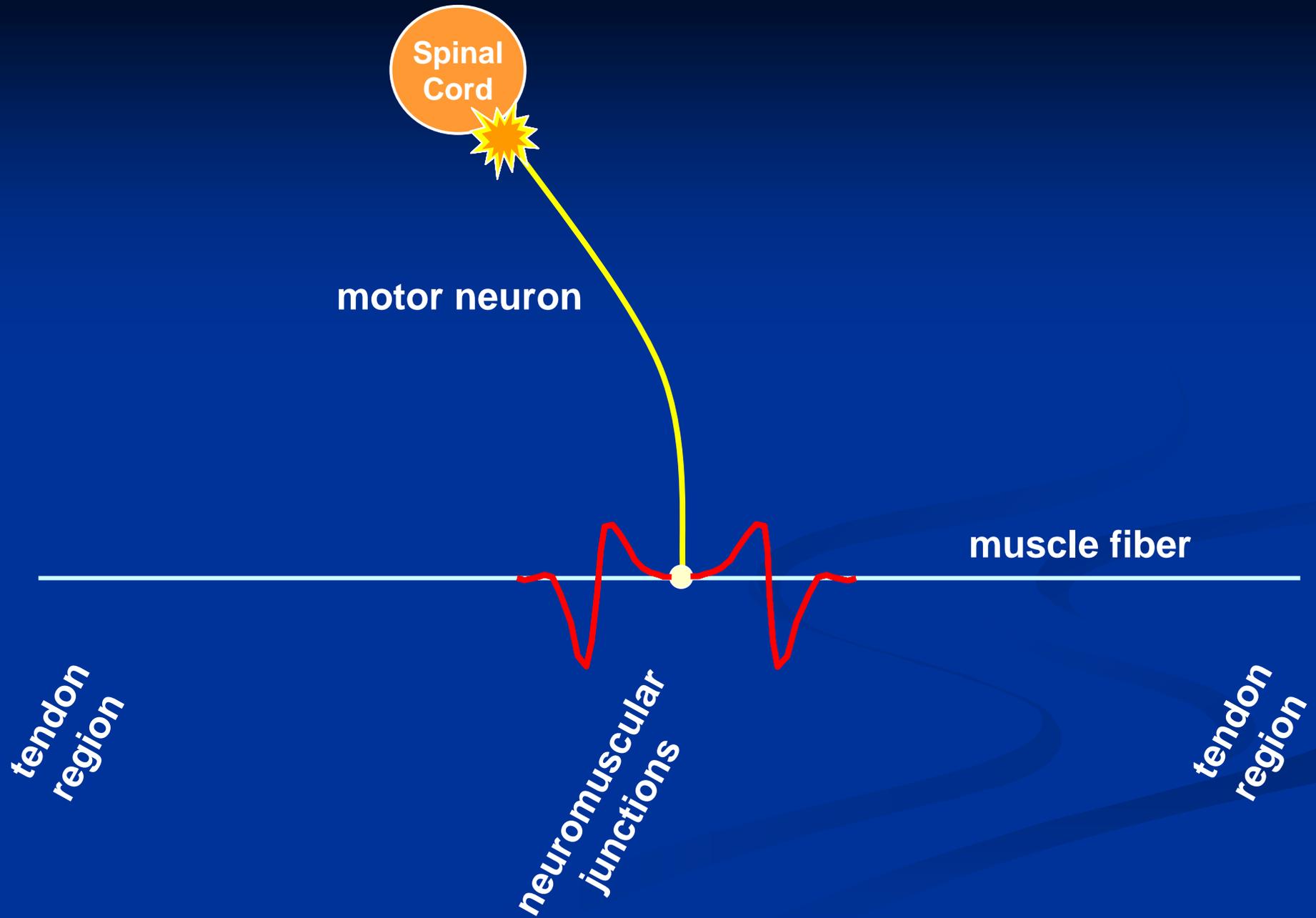


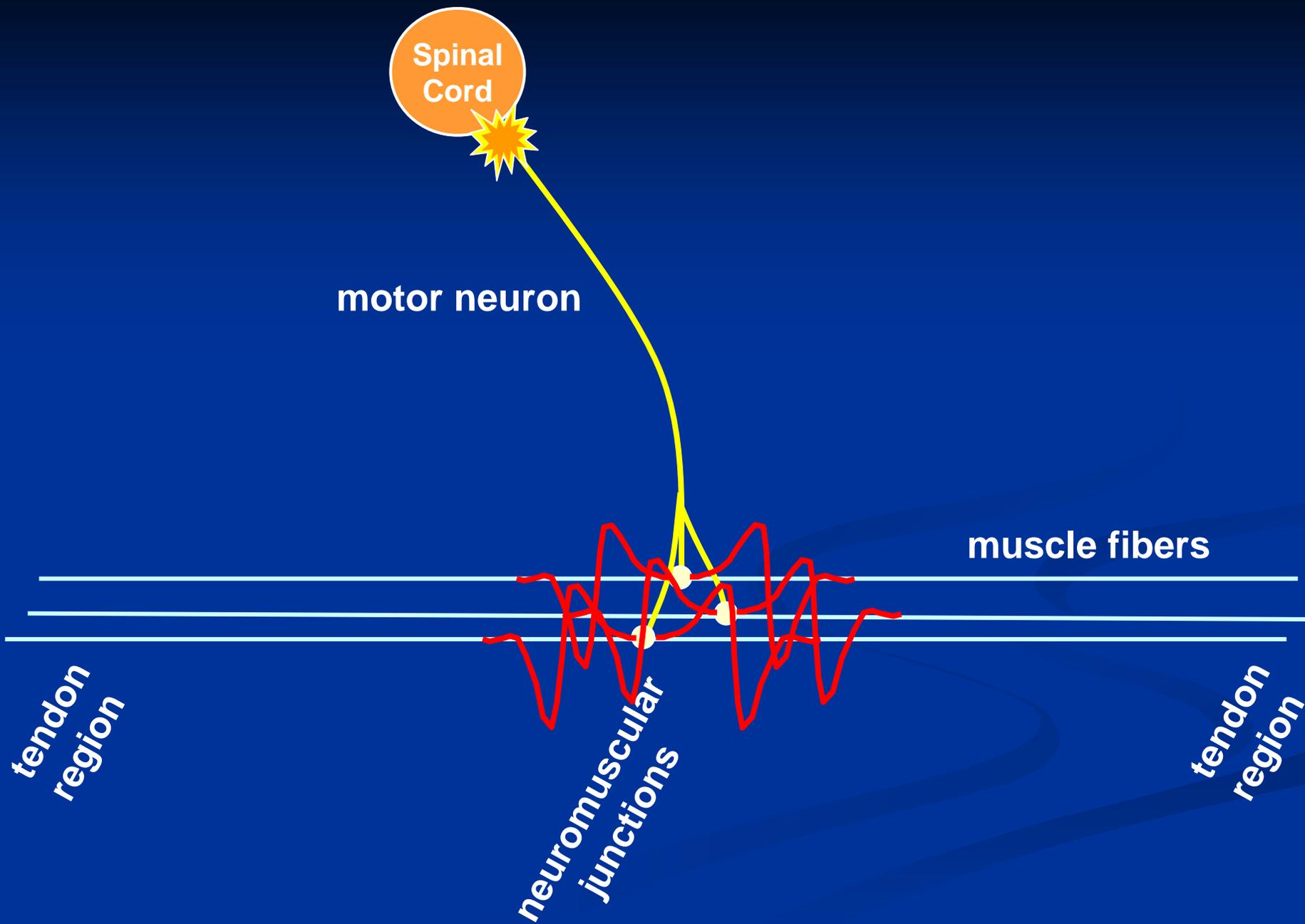
Detection of Neuromuscular Diseases Using Surface Electromyograms

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Surface EMG generation process





motor neuron

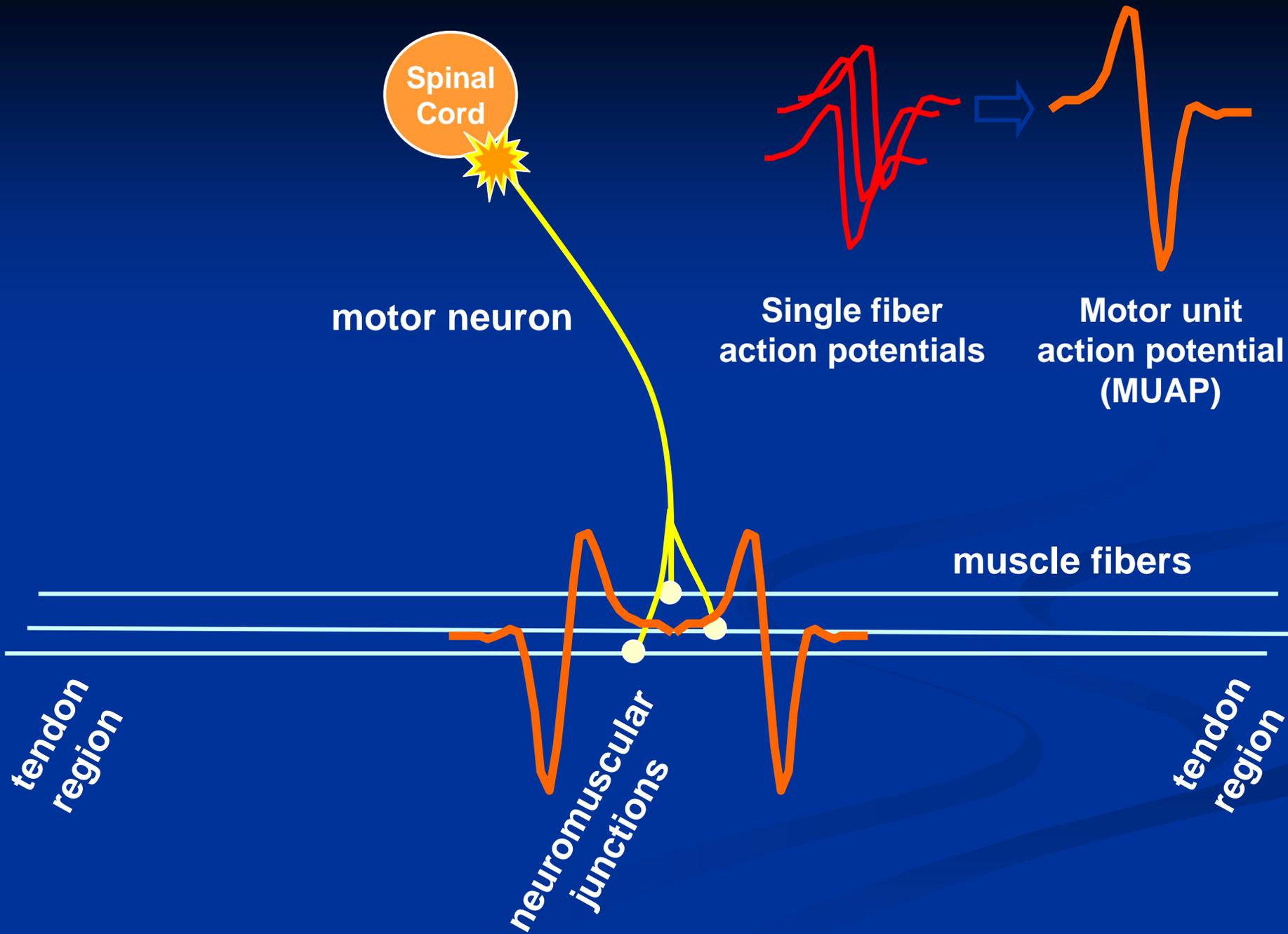
Spinal
Cord

muscle fibers

tendon
region

neuromuscular
junctions

tendon
region



Classification of Neuromuscular Disorders

Motivation

Using SEMG in the clinical diagnosis the classification to normal, myopathic and neuropathic groups of subjects can be achieved.

Neuromuscular disorders:

- myopathy - dysfunction of muscle fibres
- neuropathy - damage to the peripheral nervous system, which transmits information from the brain and spinal cord to every other part of the body

Why SEMG ?

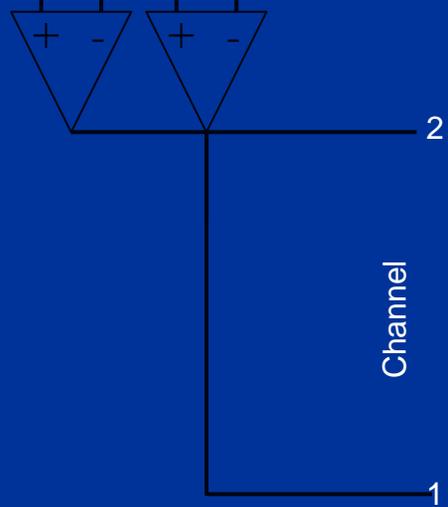
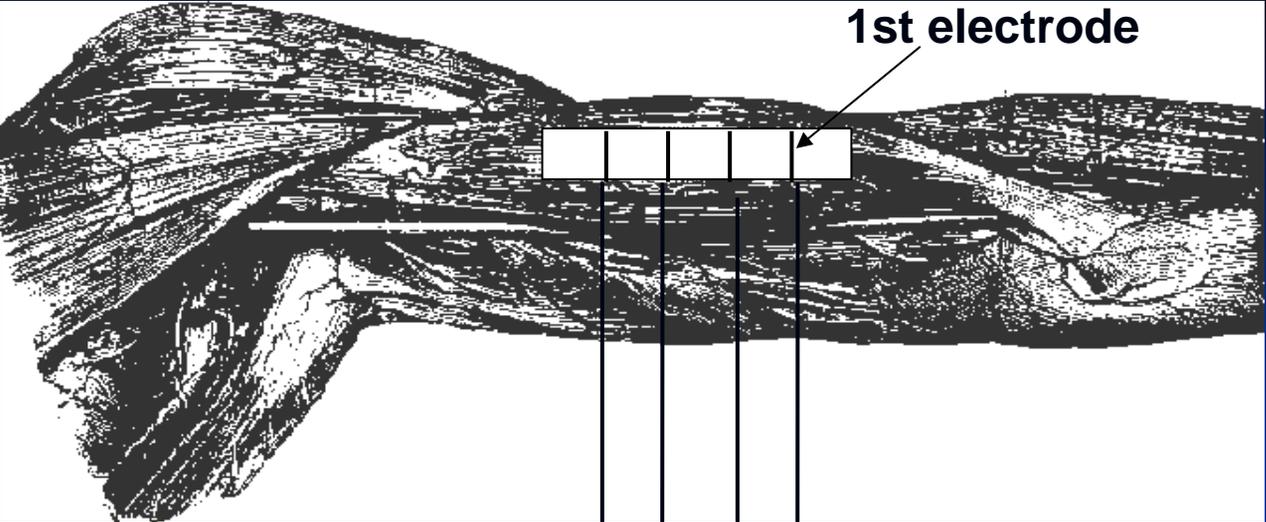
- Non invasive
- Voluntary stimulation
- User friendly
- Can be applied with the same ease on children, adults, patients
- No need for medical supervision
- Can be used nearly on any extremity muscle with minor modification

Previously used methods

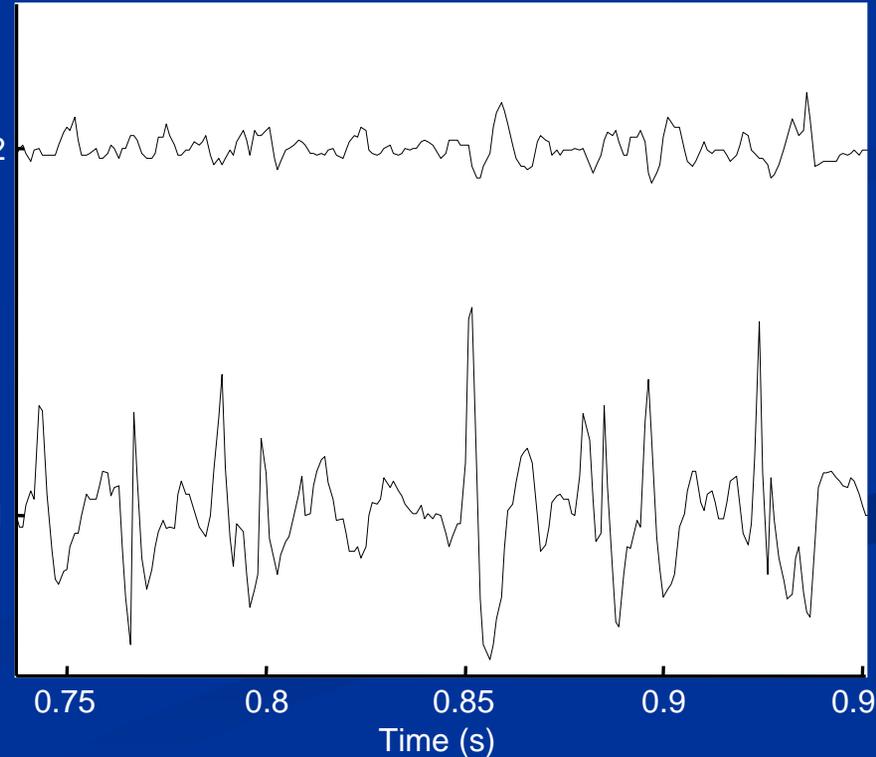
- needle EMG techniques:
 - analysis of individual MUAPs (amplitude, duration),
 - turns–amplitude analyses,
 - analysis of the firing rate of MU,
 - power spectrum analysis,...
- surface EMG techniques:
 - turns and zero-crossings per second,
 - median frequency and total power per second,
 - bispectrum peak amplitude,
 - higher order statistics,...

Data acquisition

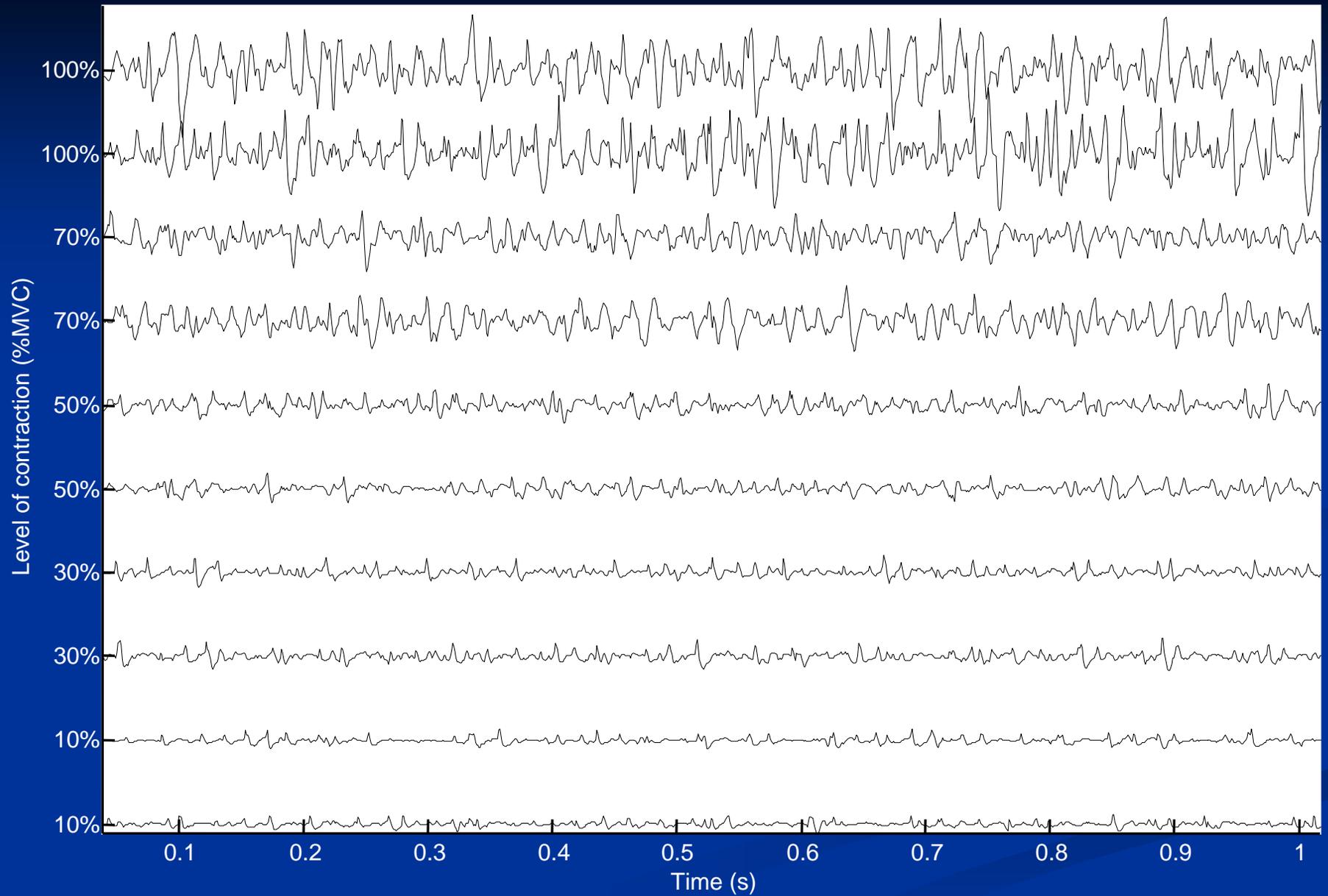
- 19 normal, 11 myopathic and 9 neuropathic subjects with the gender and age matching between normal and patient groups
- left biceps brachii muscle was examined
- four-bar SEMG active probe with an interelectrode distance of 10 mm and a bar width of 1 mm was used
- single differential recordings were recorded, one from each pair of the electrode bars
- recordings were performed for 5 seconds at 10, 30, 50, 70 and 100% of the MVC
- two trials at each force level were performed,
- band-pass filter [20÷500 Hz] was initially applied on the recorded signals that were then sampled with a sampling frequency of 1000 Hz at a 12-bit resolution.



Raw SEMG signals



Raw SEMG signals



Feature extraction

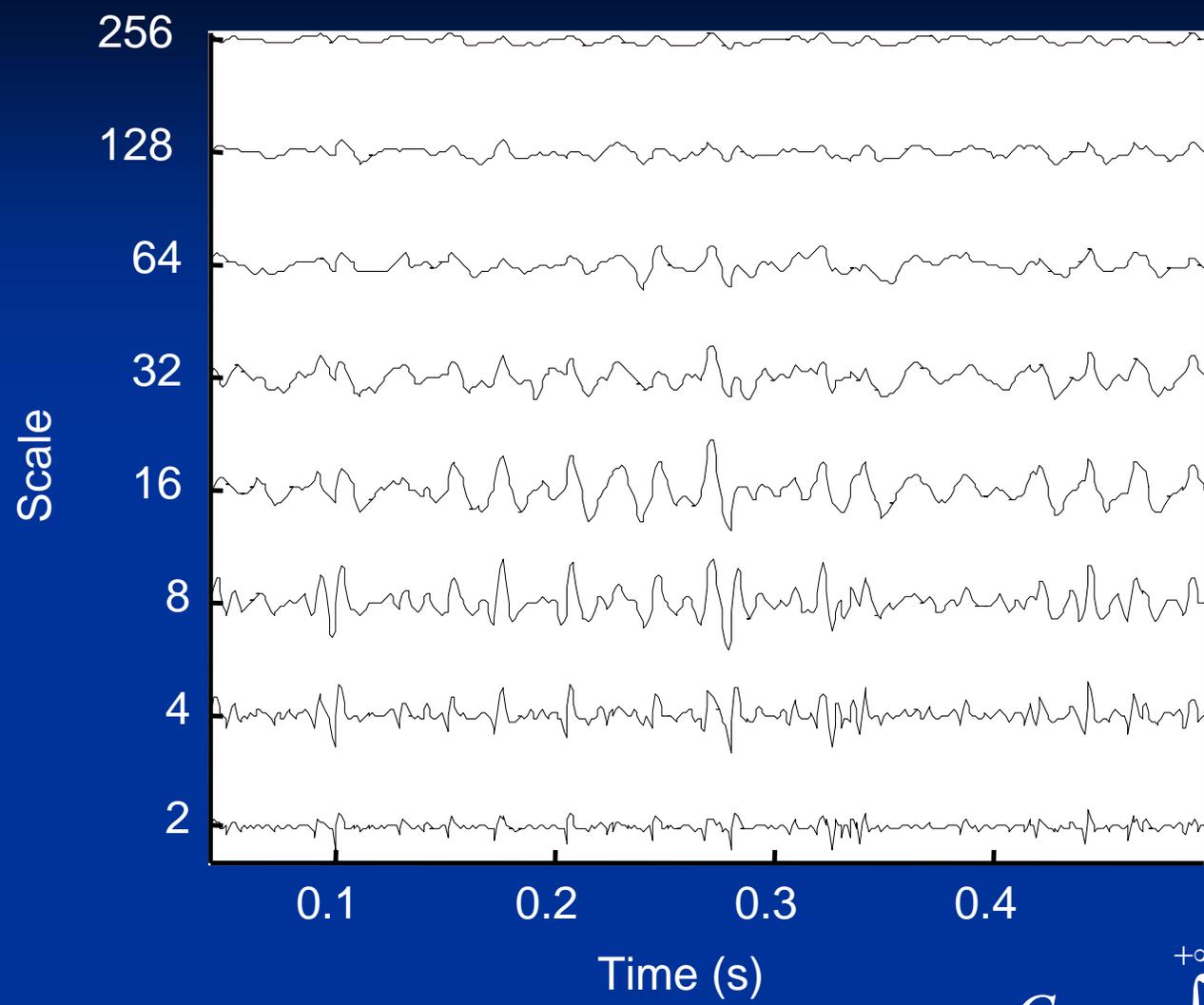
The recorded signals were further processed in order to extract some important features from them to be used in the classification process.

- totally 10 signals per person,
- each of them was transformed using continuous wavelet transform,
- diadic Haar wavelet was chosen and each signal was transformed at 8 different scales

$$2^j, j = 1, 2, \dots, 8$$

$$C_{a,b} = \int_{-\infty}^{+\infty} s(t) \frac{1}{\sqrt{a}} \psi \left(\frac{t-b}{a} \right) \cdot dt$$

Continuous wavelet transform



$$C_{a,b} = \int_{-\infty}^{+\infty} s(t) \frac{1}{\sqrt{a}} \overline{\psi \left(\frac{t-b}{a} \right)} \cdot dt$$

$$H(X) = -\sum_i P(X = a_i) \log P(X = a_i)$$

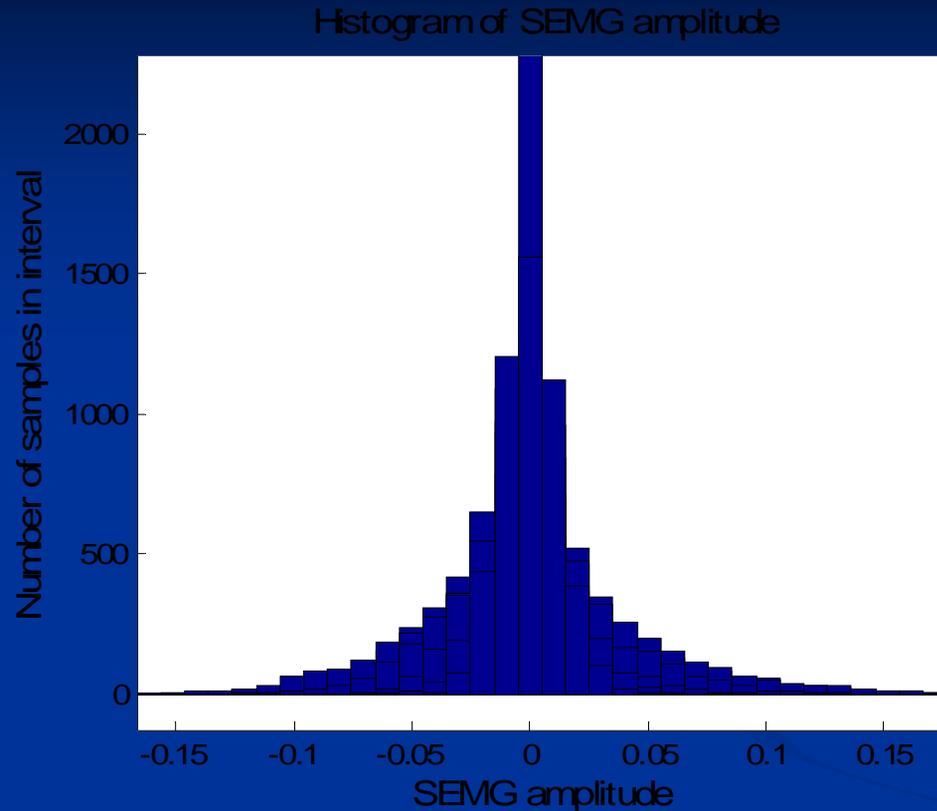
Feature extraction – step 2

- At each scale, the Shannon entropy is calculated on transformed signal:

$$H(X) = -\sum_i P(X = a_i) \log P(X = a_i)$$

- entropies of all signals have to be computed on the same interval subdivisions
- range of SEMG amplitude was [-0.4, 0.4]
- the interval was divided in 100 equally sized bins
- number of samples falling in each bin was counted for each signal (histogram)
- probability of bin is calculated as ratio of number of samples in a bin to number of all samples

Entropy



A set of 80 scalar features per subject was formed, which were base for the classification of subjects.

Classification of subjects

Classifications to the following decision classes were performed:

- normal / abnormal (myopathic and neuropathic),
- normal / myopathic,
- normal / neuropathic,
- myopathic / neuropathic,
- normal / myopathic / neuropathic.

5 different techniques from the WEKA machine learning package were used:

- decision trees j48,
- random trees,
- random decision forests,
- support vector machines (SVM),
- ensemble of support vector machine with polynomial kernel.

WEKA (www.cs.waikato.ac.nz/ml/weka/)

The screenshot shows the Weka Explorer application window. The 'Classify' tab is active. The classifier selected is 'J48 -C 0.25 -M 2'. The test options are set to 'Cross-validation' with 10 folds and a 66% split. The classifier output window displays the following information:

Size of the tree : 9

Time taken to build model: 0.03 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	144	96	%
Incorrectly Classified Instances	6	4	%
Kappa statistic	0.94		
Mean absolute error	0.035		
Root mean squared error	0.1586		
Relative absolute error	7.8705	%	
Root relative squared error	33.6353	%	
Total Number of Instances	150		

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
0.98	0	1	0.98	0.99	Iris-setosa
0.94	0.03	0.94	0.94	0.94	Iris-versicolor
0.96	0.03	0.941	0.96	0.95	Iris-virginica

The result list on the left shows the following entries:

- 16:00:27 - lazy.JB1
- 16:00:50 - lazy.JB1
- 16:01:00 - lazy.JB1
- 16:12:42 - lazy.JB1
- 16:12:51 - lazy.JB1
- 16:14:17 - trees.J48
- 16:14:32 - trees.J48

The status bar at the bottom shows 'OK' and a 'Log' button.

Results

- Resulting classifiers were obtained using 3-fold cross validation with 50 iterations for every machine learning technique
- SVM and SVM ensemble performed the best, although decision trees with human readable knowledge representation were only slightly less accurate
- Since datasets decision classes are biased, we applied the receiver operator characteristic (ROC) to measure the classifier quality

Results

Decision classes	No. of classes	Number of subjects per class	Classification accuracy(standard deviation)[%]				
			Decision trees j48	Random trees	Random forests	SVM	SVM ensemble
normal/abnormal	2	24 / 15	56.36(8.80)	55.74(12.28)	60.15(12.16)	63.90(11.02)	63.18(10.22)
normal/myopathic	2	22 / 8	68.69(11.20)	64.95(12.66)	70.68(9.32)	73.33(6.60)	71.85(9.71)
normal/neuropathic	2	21 / 7	73.52(11.19)	66.05(14.12)	70.55(11.60)	79.03(7.71)	78.09(10.08)
myopathic/neuropathic	2	8 / 7	48.67(19.17)	47.20(22.62)	46.13(16.54)	47.47(19.94)	43.07(19.90)
normal/myopathic /neuropathic	3	24 / 8 / 7	51.69(11.06)	44.82(12.56)	53.54(10.62)	62.50(7.42)	60.26(8.89)

Conclusion

- The SEMG signals in patients with the neuromuscular diseases can vary evidently depending on the stage of the disease
- SEMG-based diagnosing is not enough, other tests, such as muscle biopsies, blood tests, or genetic testing, should also be carried out
- myopathy can affect only individual muscles, while the properties of other muscle can remain unchanged
- Since SEMG measures the superimposed electrical activity of all the MUs under surface electrodes, the deviating MUs can be hidden among healthy ones
- method could be improved using an appropriate decomposition technique to extract individual MUAPs from the SEMG