Classification of acoustic emission signals in material defectoscopy based on statistics and machine learning

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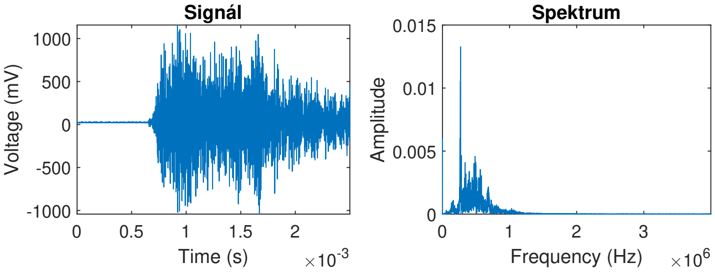
Signal

- Pretrigger, noise treshold, recording frequency 4 MHz
- Spectrum obtained through FFT

$$S_f = \frac{|\tilde{S}_f|}{\sum_{f=0}^{T-1} |\tilde{S}_f|}$$



Obrázek: Example of accoustic emission signal and its spectrum

Signal attributes

- Attribute M:

$$M = \arg\max_{t \in [0, T-1]} |x_t|$$

- Attribute P:

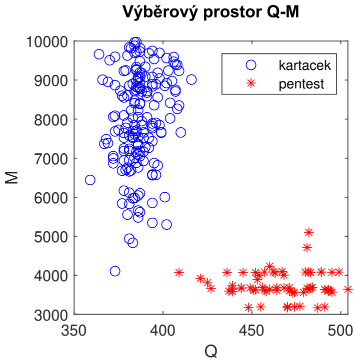
$$P = \frac{1}{T} \sum_{f=0}^{T-1} f\, S_f$$

- Attribute Q_β:

$$Q_\beta = \min \left\{ F \in [0,\, T-1] : \sum_{f=0}^{F} |X_f| \geq \beta \right\} \quad \text{pro} \;\; \beta \in (0, 1)$$

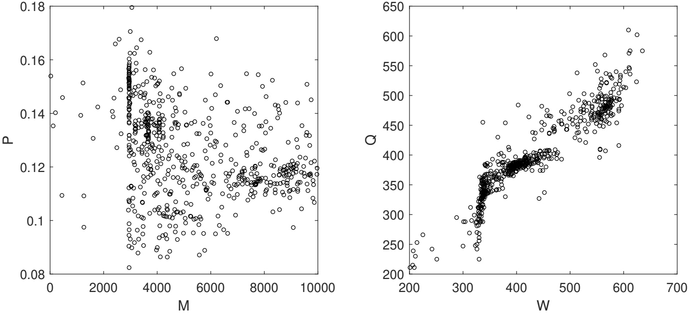
- $Z_c, W_\alpha, S_\gamma,$

Attribute comparison



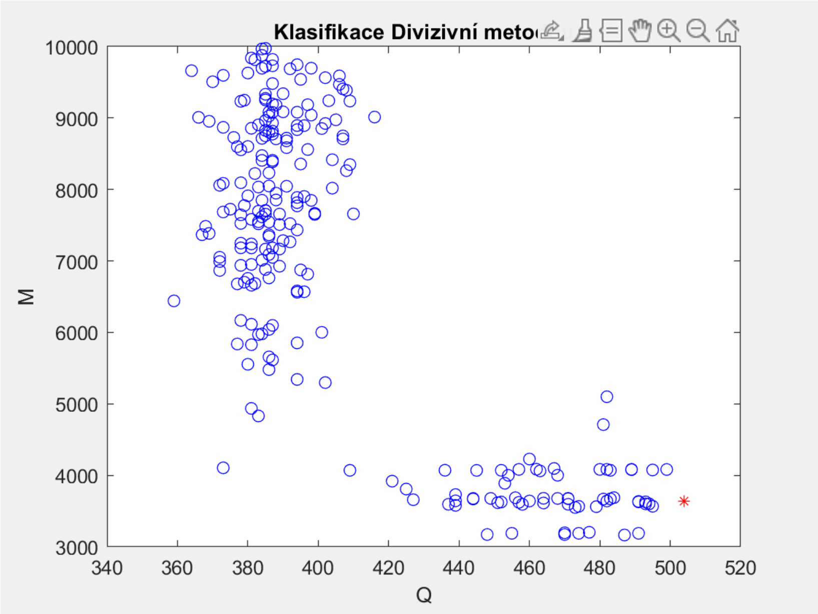
Classification

- Processed cloud of data $\{x_1, \ldots, x_n\} \subset \mathbb{R}^p$
- Supervised $\times$ unsupervised methods
- Determining number of clusters



Obrázek: Examples of data clouds

Divisive method



Model Based Clustering

- Distribution mixture: $p(x) = \sum_{j=1}^{M} \alpha_j p_j(x)$, where $\sum_{j=1}^{M} \alpha_j = 1$
- Only considering normal distribution $p_j = p_j(x|\theta_j)$
- We maximize likelihood

$$L(\theta_k, \tau_k, z_{ik}|x) = \prod_{i=1}^{n} \prod_{k=1}^{M} \tau_k^{z_{ik}} p_k(x_i|\theta_k)^{z_{ik}},$$

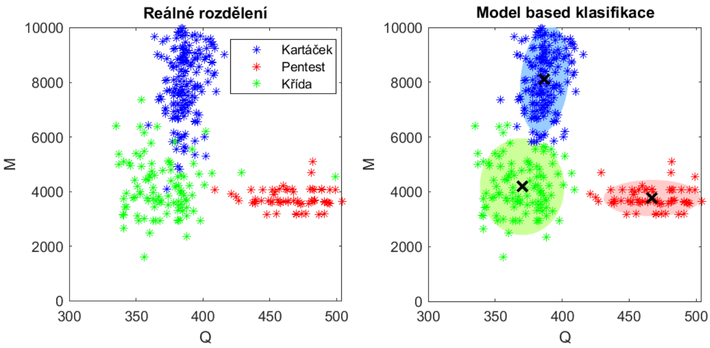
$$\text{where } \tau_k \geq 0, \forall k \in \widehat{M} \quad \& \quad \sum_{k=1}^{M} \tau_k = 1$$

- Unknown $z_{ik} \Rightarrow$ EM algorithm, we maximize

$$E_z(l(\theta_k, \tau_k, z_{ik}|x)|\theta_k, \tau_k, x)$$

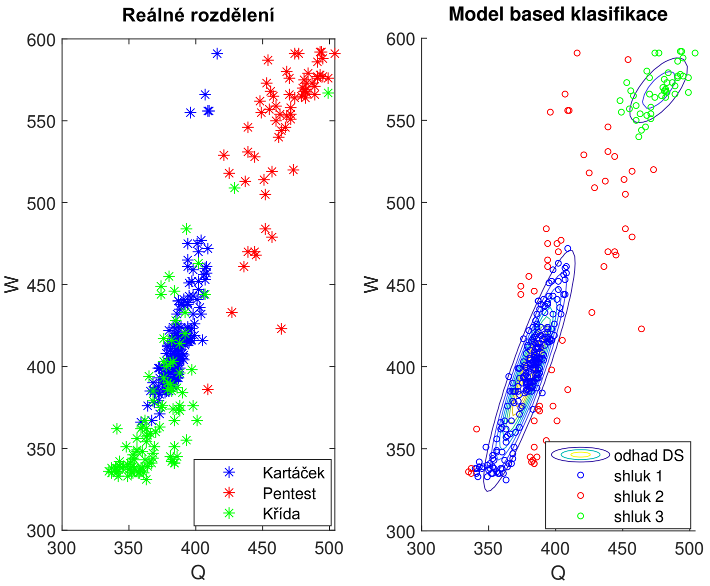
- Training data sets $T_i \quad i \in M \qquad M = \#\text{cluters}$

Model Based Clustering

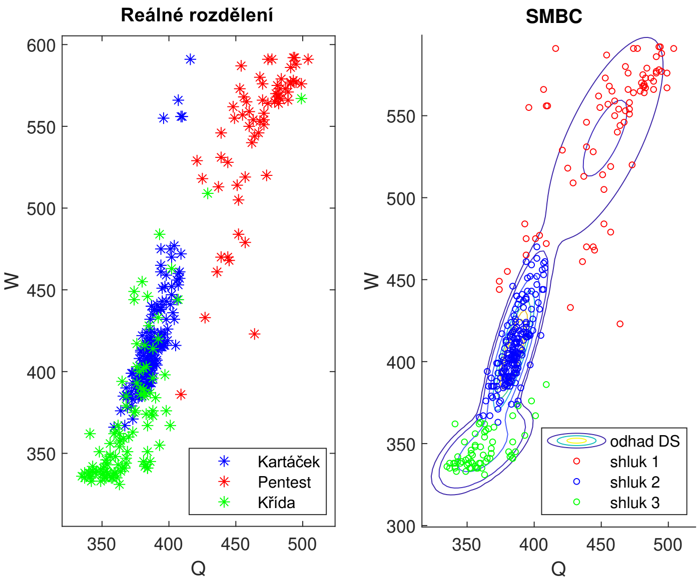


Obrázek: Classification using MBC

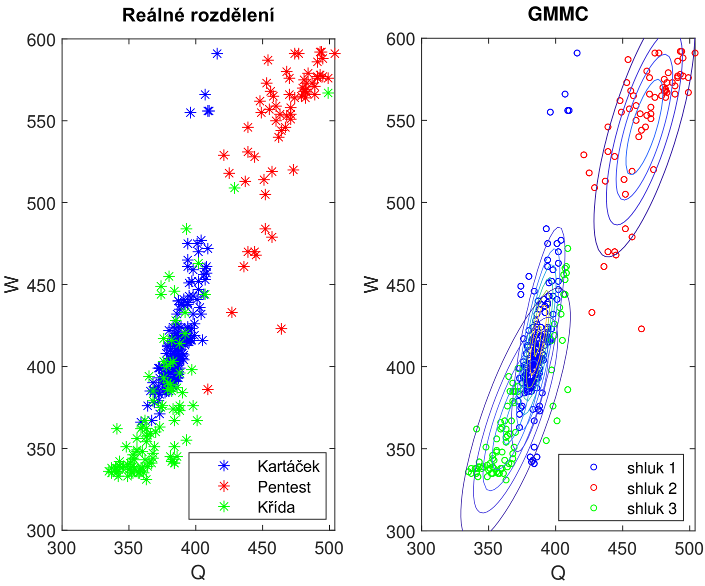
Model Based Clustering



Supervised Model Based Clustering



Gaussian Mixture Model Clustering



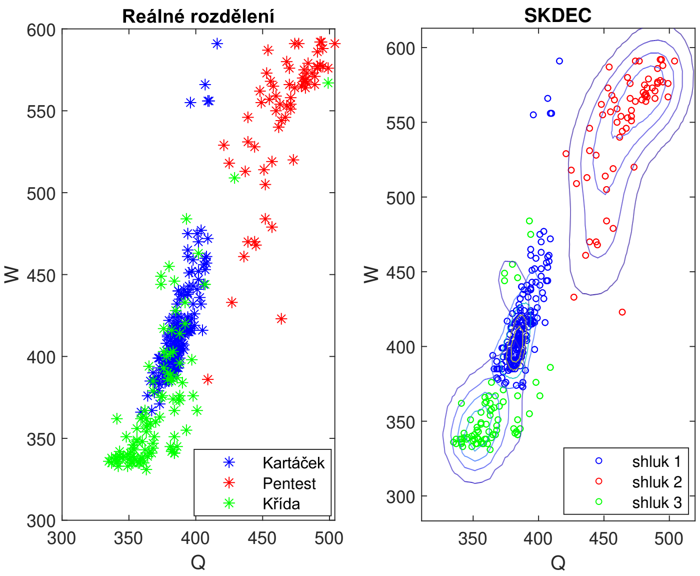
Supervised Kernel Density Estimation Clustering

- We estimate kernel densities

$$\widehat{f}_i(t) = \frac{1}{n_i h} \sum_{j=1}^{n_i} K\left(\frac{t - t_j}{h}\right) \quad i \in \widehat{M},$$

  where $t_j \in T_i$, M is $\#$ clusters.
- We calculate values $\widehat{f} = \left(\widehat{f}_1(x_j), \ldots, \widehat{f}_M(x_j)\right)$ in each point we classify
- x_j belongs to k-th cluster if $k = \arg\max_{j \in M} \widehat{f}_j(t)$

Supervise Kernel Density Estimation Clustering



Supervised Divergence Decision Trees

- Binary classification into classes $\omega_S \times \omega_B$
- In each node
  1. Density estimation on different attribute spaces
  2. Minimalization of Rényi divergence between w_S, w_B density estimates
  3. KDE separation of data
  4. Spliting data into two children
- We apply binary classification to each type of signal against the others
- Result is a $n \times M$ matrix of probabilities that x_i belongs to j-th cluster

Comparison

- Results of classification in % of correctly classified signals

	DIV	MBC	SMBC	GMMC	SKDEC	SDDT
2 soubory [M,W]	97,48	96,64	99,16	100	99,16	96,64
5 souborů [P,Z]	X	81,40	88,70	92,03	91,03	89,20