

The detection of cavitation in hydraulic machines by use of ultrasonic signal analysis

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Abstract. This presentation describes an experimental approach for the detection of cavitation in hydraulic machines by use of ultrasonic signal analysis. Instead of using the high frequency pulses (typically 1MHz) only for transit time measurement different other signal characteristics are extracted from the individual signals and its correlation function with reference signals in order to gain knowledge of the water conditions. As the pulse repetition rate is high (typically 100Hz), statistical parameters can be extracted of the signals. The idea is to find patterns in the parameters by a classifier that can distinguish between the different water states. This classification scheme has been applied to different cavitation sections: a sphere in a water flow in circular tube at the HSLU in Lucerne, a NACA profile in a cavitation tunnel and a Francis model test turbine both at LMH in Lausanne. From the signal raw data several statistical parameters in the time and frequency domain as well as from the correlation function with reference signals have been determined. As classifiers two methods were used: neural feed forward networks and decision trees. For both classification methods realizations with lowest complexity as possible are of special interest. It is shown that three signal characteristics, two from the signal itself and one from the correlation function are in many cases sufficient for the detection capability. The final goal is to combine these results with operating point, vibration, acoustic emission and dynamic pressure information such that a distinction between dangerous and not dangerous cavitation is possible.

1. Introduction

Cavitation is generated if the static pressure in a fluid falls beneath the evaporating pressure of the fluid under constant water temperature. Cavitation bubbles emerge around germs in the fluid. These germs weaken locally the adhesive forces in the fluid which makes cavitation easier. The germs might be impurities, trapped gases or other tiny cavities. The necessary reduction of the static pressure is due to local pressure fluctuations or to an increase of the fluid velocity.

The cavitation bubbles which implode near the surfaces of the mechanical components of the machine, generate a micro-jet. This leads to high pressure and velocity peaks, which cause an abrasive and damaging effect on the components. Big cavitation bubbles or vapour regions do not generate an abrasive effect, they disturb however the flow field, can cause flow separation and therefore reduce the efficiency of the machine. Both effects are unwanted. In a hydraulic machine cavitation might occur at a variety of locations. Figure 1 lists different types of cavitation in a hydraulic machine, Avellan [1] describes the fact that different dangerous and not dangerous cavitation cannot be distinguished from operating point data as it is shown in the hill chart of Figure 2. Classical monitoring methods based on frequency content of pressure, noise and vibrational signals are described in Escaler *et al.* [2].

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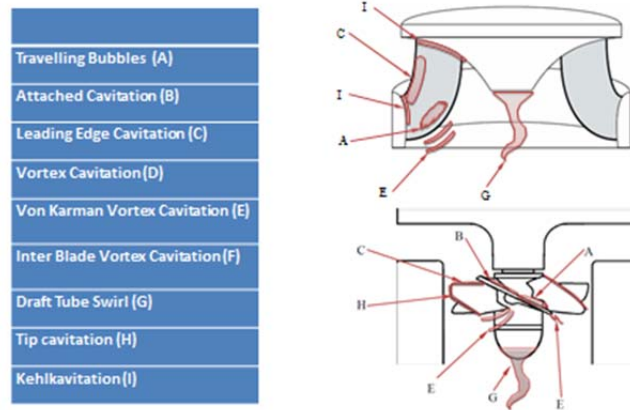


Figure 1. Different type of cavitation

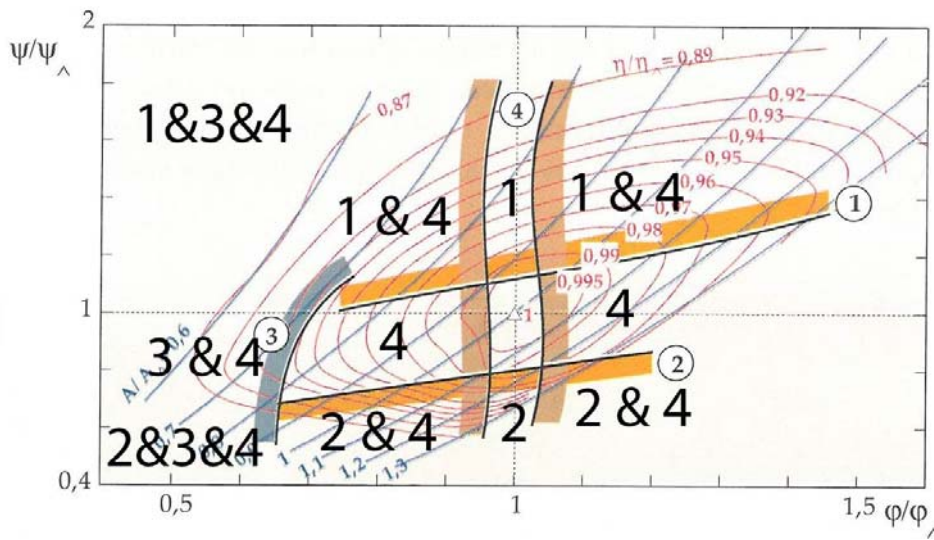


Figure 2. Hill chart for Francis turbine: regions of different types of cavitation
 1: leading edge cavitation suction side, 2: leading edge cavitation pressure side
 3: interblade cavitation, 4: ring swirl cavitation

Here a new approach is applied. The deterioration the ultrasonic signals due to the various cavitation effects is exploited in a statistical way.

2. Measurements

Measurements were carried out at three objects by mounting the acoustic sensors in a clamp-on fashion from the outside of the fluidized section of the installations (Müller [3], Gruber *et al.* [4]):

- sphere in a vertical pipe of perspex at the hydraulic laboratory at the HSLU (Figure 3)
- different profiles in the cavitation channel of the EPFL-LMH laboratory (Figure 4)
- Francis model test turbine at the test rig at EPFL-LMH (Figure 5)

Figures 3 – 5 show the three installations tested and, Figures 6 - 8 the corresponding acoustic path locations.



Figure 3. Sphere

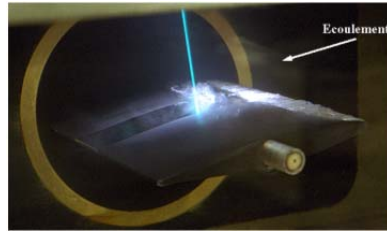


Figure 4. Profile in cavitation tunnel

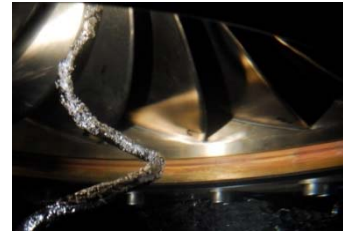


Figure 5. Francis model test turbine

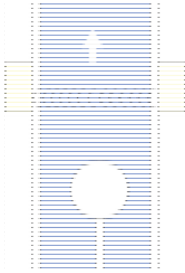


Figure 6. Acoustic path sphere

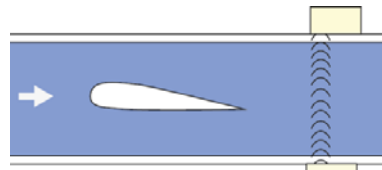


Figure 7. Acoustic path profile

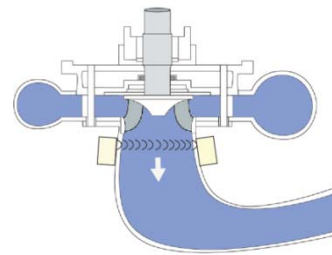


Figure 8. Acoustic path Francis turbine

The operating points of the three objects were chosen such that the different types of cavitation belonging to each operating point was visible or was known to the test engineers. Therefore the data could later be used for training the classifiers.

3. Extraction of statistical signal parameters (characteristics)

3.1 Statistical signal parameters for raw signal

For each operating points in each test section hundreds of signals (1MHz pulses) have been recorded. If they are disturbed by not ideal water conditions, various quantities of the signal change: amplitude (signal maximum), time of arrival of signal maximum, frequency content and power. As the distortions do not occur continuously in time, the different signals recorded sequentially experience different levels of distortions for the different water states. By that histograms of the above quantities can be plotted. Figure 9 shows signal examples and Figure 10 histograms of groups of 100 signals. The signals are all preprocessed to remove outliers and signals with very low signal level.

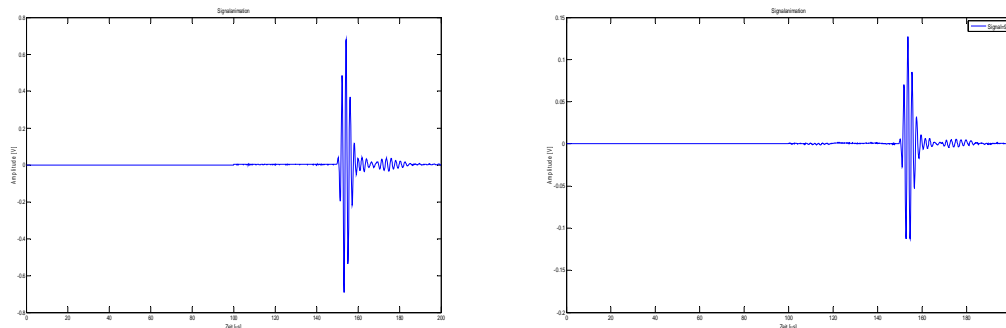


Figure 9. Samples of undisturbed signal (left) and disturbed signal

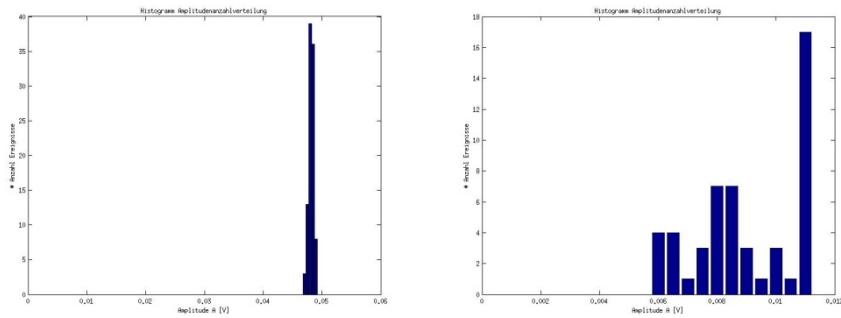


Figure 10. Histogram of 100 measurements of amplitude: left undisturbed, right disturbed (draft tube swirl)

3.2 Statistical signal parameters for correlation function

An interesting function to examine is the correlation of each incoming signal with a reference signal that corresponds to a signal obtained in undisturbed conditions. In contrast to the signal analysis of the previous section, the characteristics of two signals are used and compared to one another if correlation is applied.

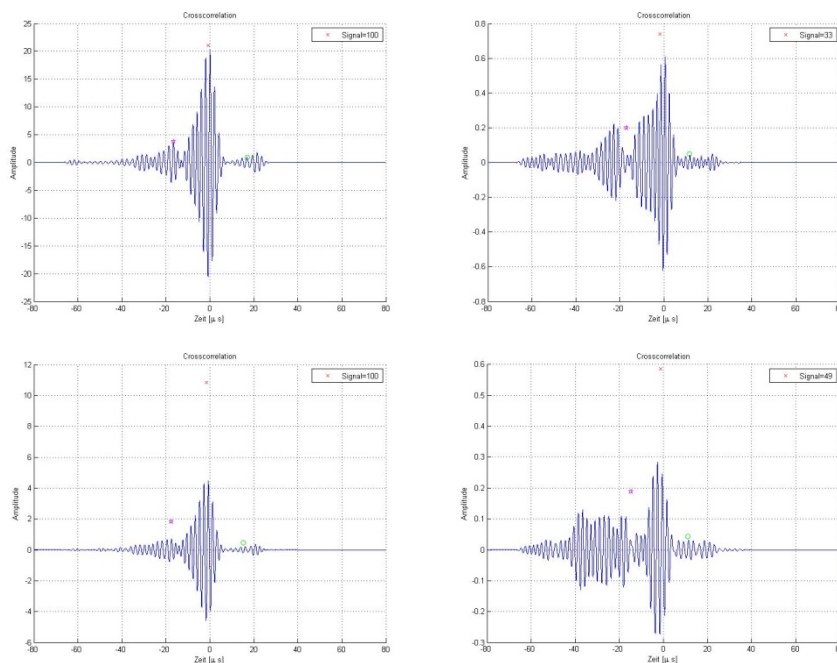


Figure 11: samples of correlation functions: upper left undisturbed signal, other signals: different degree of disturbance

3.3 Selection of important statistical parameters

The selection of the most important statistical parameters for the neural network classifiers was done in the following way:

- To begin with simple combinations and then increase complexity if needed
- For classifiers with only two inputs the selection has been done manually by looking to simple conditions including thresholds by which most of the training data can be

separated. Physical considerations were also used to support the selection process. That means not all combinations have been considered. The selected combinations have then been used for training the neural net. If several solutions were found, then no procedure was followed to make out the winner. This approach does not guarantee that a solution can be found even if one exists.

- For classifiers with three inputs the selection process gets more complex. For this study the selection has been done similar to the first case. The starting point however were combinations of two inputs which were partly successful and then adding another candidate manually. This search was again not systematically and exhaustive. If the training was successful, then maybe two or three alternatives have been tried out.

In case of a decision tree classifier, the inputs were chosen as for the neural network or they were selected by an automated search.

4. Classification with neural networks (Hassoun [5])

In order to find a neural net the following steps were followed:

- 1) Data collection and preprocessing: The collected data have to be filtered and then normalized (typically between [-1 1]). Generally it can be said, that the more data are available the better the net can be trained. Basically the net can only classify what it was trained for.
- 2) Choice of network structure: The structure including inputs and outputs has to be selected with the knowledge acquired from the recorded data, the physics behind the application and from other constraints. With the structure the number of parameters to be trained is given.
- 3) Net configuration: The configuration determines the type of learning algorithm (nonlinear optimization problem), the maximal number of iteration and the stopping error criteria.
- 4) Initialisation of weights and bias: As the optimization problem is nonlinear the solution is dependent on the initial conditions. The choice can be made between random initial conditions and fixed initial conditions.
- 5) Training: The training data are split into three groups which can be chosen in % of the whole set: the proper training data used for finding the net, validation data where undertraining or overtraining can be checked (the net is still optimized with these data) and test data for the final net. The optimization algorithm can also be chosen. Typically the Marquardt-Levenberg algorithm (Press *et al.* [6]) is used for minimizing the mean squared error function:

$$MSE = \frac{1}{N} \sum_{i=1}^N e_i^2 = \frac{1}{N} \sum_{i=1}^N (y_i - f(\underline{p}_i))^2$$

y_i = target or neural net output

$f(\underline{p}_i)$ = nonlinear mapping of neural net from inputs \underline{p} to output y

- 6) Test: The net is tested as classifier. No more training is performed.
- 7) Application: if the test is successful, the net can be applied, otherwise one has to go back to point 1) or 2).

The Matlab neural network toolbox was used for the training. The neural network approach has been tested at all three cavitation objects. In all situations the distinction between different water states was possible. In the following only one example of the Francis turbine is given.

4.1 Example: Francis turbine (Test rig, LMH Lausanne), [7], [8], [9] and [10]

This is the most complex example with a neural net with three inputs, one hidden layer with three nodes and four outputs, one for pure water, draft tube swirl cavitation, interblade vortex cavitation and leading edge cavitation respectively. The first two inputs are the mean of the amplitude and the coefficient of variation of the amplitude of the recorded signals, while the third is a characteristic from the correlation function. Two choices of characteristics of the correlation function which were successful are the ratio of mean of areas of right to left and the ratio of the mean of centre of area gravity of right and left.

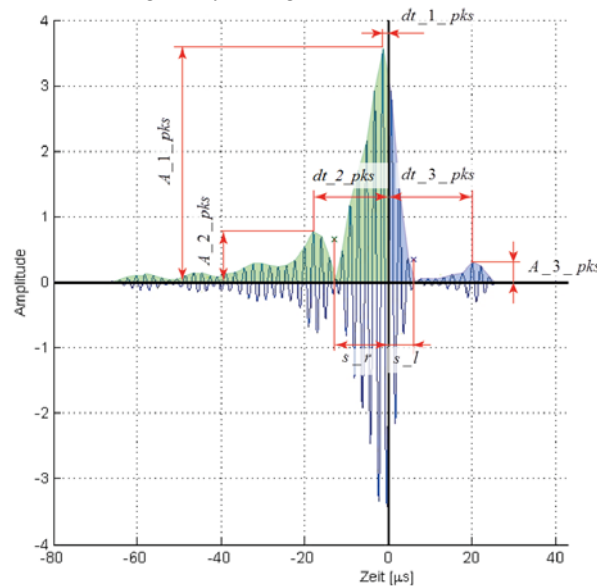


Figure 12. Definition of some parameters of the correlation function

Both are measures of the asymmetry of the correlation function. With each of the third input it was possible to distinguish all four states. Table 1 gives the details of the experiment, while Figure 13 shows the chosen network structure.

Francis Turbine (Test Rig, LMH Lausanne)

Experimental Setup	
sensor mode	direct path downstream, Clamp-On 500kHz
recorded data	5-10 x 100 samples for each state
Water state detection	
classifier	feed forward neural network
architecture	3 input neurons, 3 hidden neurons, 4 output neurons
number of weights/biases	30/10
input parameters	i) the mean of the amplitude (sample size 100) A_{mean} ii) the coefficient of variation of the amplitude $\sigma_{A,\text{rel}}$ iii) a) ratio of mean of areas of right and left of correlation function b) ratio of the mean of centres of area gravity of right and left of correlation function
Correctly detected	water (100%): W draft tube swirl (100%): DTS inter blade vortex cavitation (100%): IBVC leading edge cavitation (100%): LEC

Table 1: Data for the Francis turbine experiments, chosen neural network structure and classification results

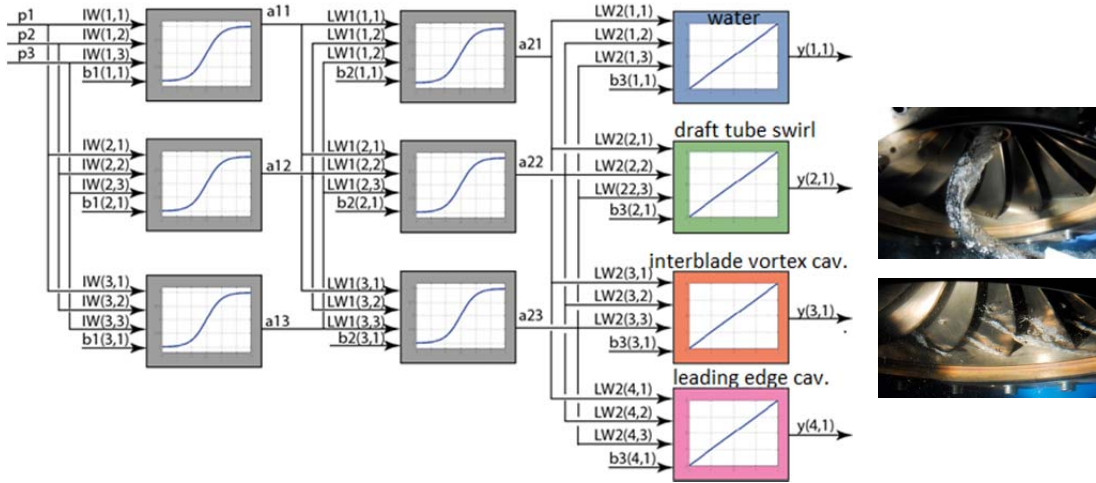


Figure 13. Neural network structure for the Francis turbine experiments

5. Classification with decision trees (Breiman *et al.* [11], [12], Hand *et al.* [13])

A binary decision tree is a sequence of conditions factored into a tree-structured series of branches as shown in Figure 14. Each node consists of a condition for one attribute or input parameter of the data set. The result of the check of the condition is either Yes or No depending on whether the attribute is above or under a certain threshold θ . Each node leads therefore to two outgoing branches. To know the order in which the attributes must be chosen to split the data in two classes, a measure is needed that allows to compare the effect of the attributes and choose then one above the other. One of these measures is called impurity and could be defined as the amount of uncertainty present in the data. The input parameter which reduces the impurity together with a threshold value for the condition in the node must be found by optimization. Given the probability p of an input parameter data set belonging to one target value, and $1-p$ the probability for the same data set belonging to the other target value, a common impurity function used in applications is the Gini index criteria

$$J(p) = p(1 - p)$$

The input parameter for which J is minimized is then chosen as the node parameter with a corresponding threshold θ . The optimization of the Gini index tries to split the input parameter data such that all the data of one input parameter for which the probability p is maximal is sent to one of the branches while all the others are sent to the other branch. The minimization of the Gini index leads therefore to pure nodes as best as possible.

5.1 Example: Francis turbine (Test rig, LMH Lausanne [14])

The same data set used before for the neural network classification is now used for the cavitation classification with a decision tree. By doing this the performance of the two different classification approaches can be compared. As the neural network used three input parameters for a successful classification, it was tried to find a decision tree classifier with the same dimensionality of the input parameters. The automated training algorithm was fed with a total of 34 parameters as input. Out of these 34 parameters the following three inputs are the minimum number in order to classify all training data correctly. The first are exactly the same as for the neural net: the mean of the amplitude A_{mean} , and the coefficient of variation of the amplitude $\sigma_{A,\text{rel}}$. The third input parameter is related to the correlation function, it differs from the neural

net input, it is the standard deviation $\sigma_{t_2pk_xcorr}$ of the time shift of first (in amplitude) left side peak from the centre of the correlation function as shown in Figure 12. The correlation function parameter inputs: ratio of mean of areas of right and left of correlation function or the ratio of the mean of the centres of area of gravity of right and left of the correlation function which were chosen for the neural net was here not selected by the training algorithm. As training method the classregtree algorithm from the Matlab statistical toolbox was used with the optimization algorithm for the Gini index criteria.

The resulting classifier is summarized in Figure 14. The tree is lean and has only four nodes. Interestingly enough the input parameter A_{mean} was chosen twice as node parameter.

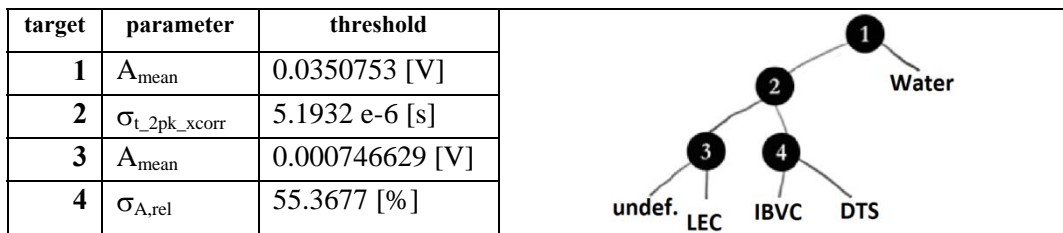


Figure 14: Used input parameters and thresholds per node and the simple decision tree structure for the Francis turbine cavitation classification by a decision tree. The undefined state consists of data, which were not associated with one of the four water states (e.g. noise only).

With the decision tree training data set, the tree structure and each branch threshold is determined. Table 2 shows the validation matrix, for which a much larger data set including training data set is classified by the decision tree shown in Figure 14.

The cavitation detection is correct except for one state which is out of the diagonal where inter blade vortex cavitation is classified as a draft tube swirl. This leads to a success rate of 98% compared to 100% with the neural network presented above for the same data set. However, compared to the neural network, the architecture of the decision tree is much simpler and more transparent. It can be easily implemented by simple rules.

		classification			
		W	DTS	IBVC	LEC
target	W	18	0	0	0
	DTS	0	8	0	0
	IBVC	0	1	11	0
	LEC	0	0	0	12

Table 2: Validation matrix, target versus classification

6. Comparison and conclusions

In order to compare the two classifier approaches in a fair way, the same procedure should be used. In the case, this was not accomplished fully. For the neural net classifier no automated selection procedure of the input parameters was applied compared to the decision trees approach. In spite of this, some important conclusions can be drawn from the results of all the experiments:

6.1 Neural net

- The neural feed forward net leads to a nonlinear mapping between inputs and target with the typical quite general interconnected structure. This enhances the chances to find a classifier which is able to distinguish the classes with high reliability. The solution found shows a complicated structure and might therefore have small robustness if applied to new data.

- The structure of the neural net must be specified before the training algorithm is applied. Here a pragmatic approach has been used and the standard neural feed forward net was selected. Physical rules of thumbs were only used for the number and the selection of the input parameters. If however, more physical insight to the observed parameters of the process to be classified is possible, then this knowledge should be used to define a more sophisticated structure of the net. That implies the number and choice of input parameters, the number of layers and the number of nodes per layer of the net. This would also allow to build a neural net that could consist of several smaller neural nets in a cascade.
- The number of weights and thresholds to be optimized gets soon pretty large with no clear connections to the underlying physics. This makes it hard to interpret the resulting function of the classifier.
- The high number of weights and thresholds leads to a nonlinear optimization problem of high dimensionality. The choice of initial conditions for the optimization is therefore a delicate issue because the found solution depends on them.

6.2 Decision tree

- In a decision tree approach only the binary node type but not the detailed tree structure is given. The training algorithm can choose the number and the selection of input parameters automatically and the detailed structure of the tree is part of the solution.
- The found decision tree is understandable, easy readable and implementable. The tree creates after each branch a subspace, whereas a feed forward neural net tries to classify all data in one space with the dimension of the numbers of different parameters. A graphical interpretation is therefore easy.
- An input parameter can be used several times which is not possible with a single feed forward neural network.
- From a decision tree we learn directly which input parameter can split best one class from the other classes. Also the threshold for each parameter condition has a physical meaning.

6.3 Conclusions

Both classifier methods are applicable and led to the required distinction of the different water states. For all the experiments at least one classifier could be found with both methods. The solutions however are not unique and are driven by the training data. The decision tree approach is easier interpretable and therefore its acceptance is higher. The method provides the user automatically with the most important input parameters. From this point of view, the decision tree method could also be used for the choice of input parameters for a neural network approach. A general automated search for the best inputs and structure of a neural net is huge and could not be carried out. The most important input parameter found have a physical meaning:

1. The attenuation observed in the mean of the signal amplitudes can be explained by the concentration and size of particles or bubbles in the water.
2. The coefficient of variation of the signal amplitude and therefore also the standard deviation can be interpreted by a concentration of cavitation or air bubbles. If there is

only a small amount of bubbles, the standard deviation is small and increases with a higher bubble concentration. If there are only a few bubbles, most of the sent ultrasound signals are unaffected. So for the most part of the recorded signals, there is no difference to a signal sent through clear water – consequently the few disturbed signals by bubbles have only a small impact on the standard deviation. Interesting is the fact that air filled bubbles influence the standard deviation much more than vapor filled bubbles – this helps to distinct air bubbles from cavitation bubbles in the water.

3. On the other hand, the physical impact on the cross correlated signals is not so clear, but with large measurement series and well defined boundary conditions, relations from water states to signal interaction can be extracted experimentally. The important cross correlation parameters describe the distortion of the shape of the signal.

Both classification methods will be applied in a next step to field experiments. An open issue is the question of how generic a classifier can be specified and how much of the classifier has to be trained on site. A special focus will also be given to the combination of the ultrasonic classifier in combination with operating point information and analysis of vibrational, hydrophone and noise signals. By merging the different sources of information by rule based or decision tree methods the chance to be able to separate dangerous from not dangerous cavitation will increase.

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