SIGNAL PROCESSING FOR NON-DESTRUCTIVE TESTING OF RAILWAY TRACKS

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Abstract. Increased speed, heavier loads, altered material and modern drive system concepts result in an increasing number of flaws in rails. Caused by the rapid change in damage mechanism by modern rolling stock the appearance of the flaws also alters. Hence, interpretation of non-destructive rail testing results may become difficult. Caused by the changed interplay between detection method and flaw the recorded signals will result in an unknown type for the rail flaws type classification. Methods for automatic rail inspection according to defect detection and classification have been developed continuously. Signal processing is a key technology to master the challenge of classification and maintain resolution and detection quality independently of operation speed. The basic ideas of signal processing based on the Glassy-Rail-Diagram for classification purposes will be presented. Examples for the detection of damages caused by rolling contact fatigue are given. Synergetic effects of combined evaluation of diverse inspection methods are shown.

INTRODUCTION

The degeneration of rails is increasing caused by the constant raise of loads and amount of overall traffic. In particular the operational speed of high speed trains, the alteration of materials used in the wheelsets and the application of modern drive system concepts result in an increasing number of flaws in rails. This causes a change in damage mechanism by the modern rolling stock and may alter the appearance of different flaw types. To guarantee the safe operation of rail traffic mechanized non-destructive inspection techniques are used in large scale to detect damages on rails. Today we face the following list of flaw types to be handled by non-destructive testing methods:

1. Headchecks
2. Defects in welds
3. SQUADs
4. Wheel burns
5. Corrugation
6. Degradation of joints
7. Kidney shaped flaws
INSPECTION METHODS

Visual non-destructive inspection of rails has been performed since the very beginning of rail traffic and is still one of the most commonly used methods. For the detection of internal flaws in the rail caused by employment or during production additional methods have been developed over time. For the detection of volumetric and crack type reflectors in the rail head, web and foot ultrasonic methods have been used since the 1950s. For the advanced detection of surface breaking and near surface defects in the rolling contact region of the rail head eddy-current methods have been developed and applied since the 2000s.

Inspection systems for manual in-service inspection using ultrasonic and eddy-current methods have been developed which allow a typical inspection speed of about 1 m/s.

For the mechanized inspection of rails rail inspection trains incorporating different non-destructive inspection methods have been build up which operate at high inspection speeds of up to more than 10 m/s. In this article we focus on the detection and evaluation of indications using ultrasonic methods in rail inspection trains.

BASIC SETUP

The basic setup for the non-destructive ultrasonic rail inspection using rail inspection trains contains a number of straight beam probes and angle beam probes operated in parallel to cover the areas of interest in the different zones of the rail. In actual setups used in the inspection trains operated by Deutsche Bahn AG typically two straight beam probes emitting longitudinal waves are used to detect reflectors which are orientated in parallel to the rails running surface and to detect the rails height. One of the both probes features a dual element setup and focusses on the rail head and reflectors close to the running surface while the other one focusses on the rail web and foot. For the detection of indications which feature an orientation non-parallel or perpendicular to the running surface angle beam probes emitting transverse waves are applied. Typ ically two sets of three angle beam probes with different angles of incidence are used in the setups to cover the angular range from +35° to +70° and -35° to -70°. For example the setup used in inspection trains operated in Germany is 35°, 55° and 70°. While the 70° probes mainly focus on the rail head, the 55° probes focus on the rail head and the web and the 35° probe covers the whole rail from the rail head to the rail foot. Supplementary ultrasonic probes may be used to cover optional areas, e.g. angle beam probes focusing on certain areas in the rail head. Figure 1 shows the setup used in SPZ1 and SPZ2 train operated by Deutsche Bahn AG.

SOUNDFIELD SIMULATION

To obtain optimal performance during inspection sound field parameters for each probe have been simulated using semi-analytical and finite elements methods. Semi-analytical models have been applied to evaluate signal response and distance amplitude curves while finite element methods have been used to evaluate wave propagation in the rail and interaction with the geometric boundary conditions of the rail. Figure 2a shows the sound field of a straight beam probe in the cross section of a rail perpendicular to the rail axis simulated using ArrayCalculus3D. Figure 2b shows the correspondent sound field of a 35° angle beam probe in the cross section along the rail axis.
For optimal probe positions and rail geometries wave propagation have been simulated to identify the positions where indication from the geometry have to be expected using the simulation tools AnSys and CIVA. During inspection the probes are aligned as close as possible to the geometrical center of the rail by the mechanical guiding system of the measurement boogie. Nevertheless dependent on the wear of the inspected rail and in curves a misalignment of the probes may occur. This misalignment causes a shift in sound travel time and echo amplitude of the received signals. For a misalignment from 0 mm to 15 mm figures 3a, 3b and 3c show wave propagation in the rail head at 6 µs, 12 µs and 32 µs. The relative acceleration of the elements is shown.
It can clearly be seen that for larger misalignments the reflections from the region of the transition from the rail head to the web become asymmetric and cause echo signals different in amplitude and travel time. Also mode conversion from longitude to transverse mode can be identified indicated by the different wavelengths and propagation velocities of the reflected pulse packets. The behavior of the indications from the rail geometry has been well understood by the use of these models.

The output from the simulations has been used to optimize the parameters for the setup of the ultrasonic system and for the setup of the data recording.

DATA RECORDING

The sound velocity in the rail and the geometry of the rail limit the maximum achievable pulse repetition rate at least by the sound travel time elapsed in the rail and probe. The lateral resolution of ultrasonic measurements is directly affected by the train speed. Therefore inspection trains are typically operated at inspection speeds as close as possible to the physical limits for the ultrasonic testing.

The high inspection speed causes a large amount of incoming data from the probes. This poses a challenge to the processing and the evaluation of the collected data, e.g. the SPZ1 operated by Deutsche Bahn AG continuously records measured ultrasound data at a repetition frequency of about 4650 Hz independent of operation speed merged with additional information, e.g. GPS, time stamps and position markers. This results in raw data volume of about 300 MB per kilometre.

GLASSY-RAIL-DIAGRAM

The detectability of defects decreases with the increase of speed. To maintain resolution and detection quality over a wide inspection speed range independent of operation speed, signal processing algorithms have to be applied. Therefore real time algorithms and the Glassy-Rail-Diagram have been developed and tested. An example image for a Glassy-Rail-Diagram is shown in Figure 4.
The Glassy-Rail-Diagram developed by BAM gives a side view from the rail like conventional B-scans. The algorithms consider the position of probes, angles of incidence of the probes and sound paths as well as the rail geometry to generate a geometry corrected diagram incorporating all A-scan and gate data from all recorded channels. The diagrams resolution respectively the size of a pixel is 3 mm by 3 mm. Two types of information are displayed in the Glassy-Rail-Diagram. A gray scale image represent the maximum amplitude recorded for each pixel while a coloured image represents the probes which recorded a significant amplitude for each pixel. For a combined display both images are overlayed.

**IMAGE PROCESSING AND DATA EVALUATION**

To support evaluation of data by the operator automated indication classification algorithms featuring ten classes have been developed and adapted, which allow preselection of data displayed during evaluation. For each of the three regions rail head, web and foot three classes have been implemented respectively. Unascertainable indications are handled in an additional class for unknown indication types.

The implemented data post processing on the recorded raw data for each rail uses a three step algorithm based on statistic methods, a neuronal network and fuzzy logic.

During processing the recorded data are segmented to 2D-clusters with a size of 64 by 64 pixels which equals an area of 192 mm by 192 mm. Overlapping of the segments is set to 50 percent. For each kilometre and each rail 10417 clusters of amplitude and probe gate data have to be evaluated.

Main foci of the implemented algorithms are the identification of indications caused by acoustic and electric noise as well as the identification of non-generic indication patterns and indication patterns caused by drill holes and welds. Rail type can be evaluated by measuring rail height.

In a first step the 2D-cluster is evaluated by statistic methods to extract the features describing this cluster. Due to the harsh environment and the boundary conditions for the inspection, recorded data will typically be incomplete up to a certain amount, will be in lack of some features or will contain unwanted information, e.g. noise. In this case using an evaluation based on statistic methods is a good choice to become stable against partial signal loss or noise from some of the sensors. For the definition of the features to be extracted from the cluster detailed a-priori information on the behaviour of the ultrasound and its interplay with defects in the rail head, web and foot region has been a mandatory input. Dependent on the region features listed below are evaluated for each cluster.

1. Histogram of amplitudes
2. Neighbourhood criteria
3. Local distributions of indications
4. Multiple indications
5. Multiple pixel hits
6. Rail height
7. Signal loss

The evaluated features will be input to the next processing step.

Based on a neuronal network pattern recognition is performed in a second step. For each 2D-cluster the feature list outputted by the statistical evaluation is analyzed by a supervised trained neuronal network to identify significant patterns. The pattern descriptors are subdivided in indication groups from geometry, indication groups from noise, indication groups from forms (e.g. drill holes and welds) and flaw type indication groups. Caused by the nature of the recorded data multiple findings of patterns in one cluster will occur.

The training of the neuronal network has been stopped at a certain stage to maintain a stable and consistent reaction of the analyzing process during inspection.

The third step of the signal processing is done by means of fuzzy logic. The pattern descriptors outputted by the neuronal network are weighted with fuzzy logic to decide for the final classification. Different rail geometries (e.g.
different rail heights), unstable signal quality, incomplete data sets and multiple findings have to be covered during evaluation. These boundary conditions will not allow sharp detection thresholds. For the avoidance and reduction of false calls decision rules on the pattern descriptors for the final classification have to be rather soft and floating. Therefore the applied fuzzy logic algorithm is designed to balance the probabilities of selected options for each class. Design of the algorithm has been done incorporating a-priori information based on expert knowledge.

CLASSIFICATION EXAMPLES

To demonstrate the performance of the algorithms three examples are given. Each Glassy-Rail-Diagram image shows about one meter of one rail. The first example in Figure 5 shows a typical thermite weld flanked by two drillings one to the left and one to the right at the ends of the rail. The data evaluation has detected at least four relevant indication patterns for classification. Indication one and three have classified as drilling in the rail web with 75% of possible features detected. Indication two has been classified as weld with 66% of possible features detected. Indication 4a and 4b have been identified as noise with a threshold of 25%. The proposal for evaluation to the operator is drilling, weld, drilling for the affected positions in the clusters.

Figure 5: Example Glassy-Rail-Diagram evaluation drillings and weld

Example two in figure 6 shows the typical indication of one defect of type SQUAD in the very middle position of the image. Maybe there is a second SQUAD in the right area of the image but signal amplitude has been too low to trigger the hardware gates so the signal is only displayed in the grey-scale image but no signal has been recorded in the gate data set. The data evaluation has detected two relevant indication patterns. Indication one has been classified as defect in the rail head with 100% of possible features. Indication two has been classified as unascertainable indication. The probability for classification weld and for classification defect in rail head has been 50%. Caused by the lack of gate data for this region in the rail head and a loss of backwall indication, the fuzzy logic decided to sort the indication to unascertainable indication for the affected cluster which has to be decided on by the operator.

Figure 6: Example Glassy-Rail-Diagram evaluation SQUAT

Example three given in figure 7 shows a very noisy section of data. This typically occurs when the train wheels are generating audible high frequency noise, which generates surface waves in the rails overlaying the ultrasound signals received by the probes. In this section there are two drillings present. These drill holes are typically used for the mounting of ground connections. In all clusters noise indication pattern has been detected and classified with 100% of possible features. Indication two and three have been classified as drilling in the rail web with 87% of possible features for indication two and 75% for indication one. Both drillings two and three are marked with a cursor for distance measurement in the affected clusters.
CONCLUSION

Rail defects and their detection pose a challenge to the safe operation of rail traffic since the beginning of the railway age. Damage mechanism and their appearance have been altered over time due to different materials, loads and gear used.

Mechanized ultrasonic rail inspection carried out with rail inspection trains acquires huge amounts of inspection data which has to be processed and evaluated by the means of signal processing. Caused by the large operation speed span of the train and harsh environment conditions, the recorded data have a variation in signal quality. Using a three step evaluation based on statistic methods, a neuronal network and fuzzy logic algorithms become stable against variation. For the classification of the recorded data on clusters taken from the Glassy Rail Diagram in a first step statistic methods are applied to extract features for further evaluation. Data analysis and classification algorithms based on a neuronal networks followed by fuzzy logic, implemented with expert knowledge reporting ten classes, give support to the operator when evaluating measured data with the Glassy-Rail-Diagram. Three examples have been shown and the performance of the algorithm has been demonstrated.

For the future the next step shall be an estimation for the probability of detection (POD) and for the probability of classification (POC) calculated by the algorithm itself based on the evaluated data set. Due to the number of different rail types and rail profiles as well as the constant change of operating conditions, the adaptation and optimization of system setups and algorithms is still an ongoing process.

ANNOUNCEMENTS

Special thanks goes to Rainer Boehm and Yannick Wack from BAM who supported this work with their simulations using ArrayCalculus3D, AnSys and CIVA.

REFERENCES

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