MACHINE VISION FOR AUTOMATIC VISUAL INSPECTION OF WOODEN RAILWAY SLEEPERS USING UNSUPERVISED NEURAL NETWORKS

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Master Thesis Computer Engineering 2009

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# DEGREE PROJECT

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**Title**

Machine Vision for Automatic visual inspection of wooden railway sleeper using unsupervised neural networks

**Keywords**

Artificial intelligence; Non-destructive testing; Rail inspection; Rail transportation; Unsupervised learning; Data fusion
ABSTRACT
The motivation for this thesis work is the need for improving reliability of equipment and quality of service to railway passengers as well as a requirement for cost-effective and efficient condition maintenance management for rail transportation. This thesis work develops a fusion of various machine vision analysis methods to achieve high performance in automation of wooden rail track inspection.

The condition monitoring in rail transport is done manually by a human operator where people rely on inference systems and assumptions to develop conclusions. The use of conditional monitoring allows maintenance to be scheduled, or other actions to be taken to avoid the consequences of failure, before the failure occurs. Manual or automated condition monitoring of materials in fields of public transportation like railway, aerial navigation, traffic safety, etc, where safety is of prior importance needs non-destructive testing (NDT).

In general, wooden railway sleeper inspection is done manually by a human operator, by moving along the rail sleeper and gathering information by visual and sound analysis for examining the presence of cracks. Human inspectors working on lines visually inspect wooden rails to judge the quality of rail sleeper. In this project work the machine vision system is developed based on the manual visual analysis system, which uses digital cameras and image processing software to perform similar manual inspections. As the manual inspection requires much effort and is expected to be error prone sometimes and also appears difficult to discriminate even for a human operator by the frequent changes in inspected material. The machine vision system developed classifies the condition of material by examining individual pixels of images, processing them and attempting to develop conclusions with the assistance of knowledge bases and features.

A pattern recognition approach is developed based on the methodological knowledge from manual procedure. The pattern recognition approach for this thesis work was developed and achieved by a non-destructive testing method to identify the flaws in manually done condition monitoring of sleepers.
In this method, a test vehicle is designed to capture sleeper images similar to visual inspection by human operator and the raw data for pattern recognition approach is provided from the captured images of the wooden sleepers. The data from the NDT method were further processed and appropriate features were extracted.

The collection of data by the NDT method is to achieve high accuracy in reliable classification results. A key idea is to use the non supervised classifier based on the features extracted from the method to discriminate the condition of wooden sleepers into either good or bad. Self organising map is used as classifier for the wooden sleeper classification.

In order to achieve greater integration, the data collected by the machine vision system was made to interface with one another by a strategy called fusion. Data fusion was looked in at two different levels namely sensor-level fusion, feature-level fusion. As the goal was to reduce the accuracy of the human error on the rail sleeper classification as good or bad the results obtained by the feature-level fusion compared to that of the results of actual classification were satisfactory.
Acknowledgement

This work was supported by the Department of Computer Engineering at Dalarna University. It gives me great pleasure to thank my supervisor Dr. Siril Yella, for motivating this project work. Without his time and effort I would not have been able to successfully complete my thesis work.

I would also like to acknowledge Prof. Mark Dougherty, Dr. Pascal Rebreyend and all other lecturers in the Computer’s Department of Dalarna University for providing all the resources required to complete my thesis work. I am also thankful to all my classmates, for their help during my studies.
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1 Introduction

The visual inspection of the material for quality maintenance is required in any field of business to succeed. Condition monitoring is one method that can offer effective approaches for sleeper material quality maintenance in railways. Now-a-days the transport industries have widely adopted condition monitoring routines in many of its subject areas with the main purpose to ensure safety and reliability in its day-to-day operations. The visual inspection systems are designed for detecting and classifying the defects from the surface of the material to be inspected or graded to ensure proper condition.

Rail inspection is the practice of examining rail sleepers for flaws that could lead to catastrophic failures. One of the leading causes of railway accidents is attributed to be human error in material inspection. Visual inspections are effective for the areas like rail transportation where the material to be inspected is clearly visible to the human eye and the inspections need to be performed by qualified personnel. For effective condition monitoring, inspections must be carried out routinely and inspectors need to be properly motivated to perform a thorough visual inspection.

Usually the rail sleepers are made of different materials like wood, concrete, iron and so on. The target material inspected in this project is wood of railway sleepers. On the whole fast and efficient inspection system is important to ensure the safety of railways. Traditional manual rail inspection methods include destructive techniques, such as coring, and non-destructive techniques, such as hammer sounding. The condition monitoring applications extensively deploy the usage of non-destructive testing (NDT) procedures within any transportation domain. (A Vary 1972).

Non-destructive Testing (NDT) is testing that does not destroy the test object. It is a branch of the materials sciences that is concerned with all aspects of the uniformity, quality and serviceability of materials and structures. Non-destructive inspection of rail-tracks is growing in importance as a consequence of the increase in axial load, traffic volume and travel speed.
Essentially, NDT refers to all the test methods which permit inspection of material without impairing its future usefulness. NDT incorporates all the technology for detection and measurement of significant properties. The purpose of NDT is to determine whether the material will satisfactorily perform its intended function or not. The NDT checks for discontinuity, defect, flaw, imperfection in the material under inspection. ‘Flaw’ means a detectable lack of continuity or a detectable imperfection in a physical or dimensional attribute of a part.

Preventive maintenance tells if parts are still satisfactory for use, resulting in fewer repairs, less accidents and lower over-all operating costs. Increased serviceability of equipment and materials will result through the application of NDT methods and techniques by finding and locating defects which may cause malfunctioning or breakdown of equipment. In the field of safety proper use of NDT will aid in the prevention of accidents, with their possible loss of life, property, and vital equipment.

Techniques like Artificial intelligence (AI) facilitate the purpose of automatic interpretation of NDT data using neural networks, case-based reasoning, machine vision, expert systems, fuzzy logic and genetic algorithms, etc., because the data yielded by NDT techniques or procedures are usually in the form of signals, images etc.

In this project a method is proposed for an automated rail track inspection system for finding cracks on the wooden rail sleeper. The condition of the track is recorded using a NDT method by image capturing of rail sleepers. The methodology is described in the next section which details the image processing operations involved in wooden rail sleeper inspection. The results show that highly robust wooden sleeper inspection is possible through fusion at different levels of image analysis method.

### 1.1 Purpose

One of the problems that railroads have faced since the earliest days is the prevention of service failures in track. Now days, as is the case with all modes of high-speed travel, failures of an essential
component on the track can have serious consequences. The sleeper condition is assumed to be one of the causes of track failures as the structural integrity of rail sleeper is a function of many factors such as age, fatigue stress, manufacturing defect and so on. These factors will always be present, and their effects become more pronounced as time goes on. At some point in time, rail conditions such as those mentioned go unnoticed. Even though rail inspections are performed routinely they do not demonstrate the economics desired by railroad operators.

Rail inspections were initially performed manually by visual means. Visual inspections will only detect external defects and sometimes the subtle signs of large internal problems. Developing the best maintenance method is difficult but by regular condition monitoring, sleeper with defect can be replaced to avoid troubling consequences. To avoid all the problems with wooden sleepers, they can be replaced by concrete ones, but that is also not a permanent solution and it is bigger capital investment to railways. Less maintenance costs and effective maintenance procedures will be viable for railways in providing quality of service.

The purpose of this project is to develop an automated wooden railway sleeper inspection, so that it does the condition monitoring of sleepers in faster way and also works in a cost efficient manner.

1.2 Problem formulation

In general the rail inspection is done by a human operator walking along the track and examining the sleeper by the sound analysis and visual examination. The sound analysis is done manually by hitting the sleeper with an axe and then classifying by the quality of sound produced. In both ways of manual inspection methods the classification of sleepers is based on the intuitive skills of the human operator.

Also manual inspection on each single sleepers is time consuming and tiresome which also effects the classification of sleeper by operator. The serious problem is that the necessary manual inspection is error prone. Every human has their own experience in wood detection and based on this sometimes it may not be possible for humans to discriminate between the good and bad classes of wooden rails.
1.3 Proposed solution

To completely eliminate the problems with wooden rail sleeper inspection, they can be replaced by concrete sleepers but that does not ensure to be a best solution as there can be approximately 1400 sleepers per kilometres and with over 11000 kilometres of tracks in Sweden. Replacement of sleepers depends on the country and the size of the rail sector business.

The goal of this project work is to provide a solution by automating the visual inspection of wooden rail sleepers to minimize the train accidents caused due to lack of proper inspection on sleepers and to achieve a cost efficient automated inspection method which is fast in operation and gives reliable and robust results in machine vision process of condition monitoring of rail sleepers.

The pattern recognition approach developed works on the features extracted from machine vision system. After pre-processing the data further the classifier finally classifies the target material based on features like crack length, width and number of cracks. The work done in this project is limited to inspection of wooden sleepers and cannot be applied to other types of rail sleepers as the nature of materials are different and the problems arising may also be different. The big advantage expected is that accuracy problems due to human labelling errors can be eliminated.

1.4 Relevant past work

Many of the previous works on automatic wooden rail inspections have implemented artificial neural networks with supervised learning techniques. The research on “pattern recognition for automating condition monitoring of wooden railway sleepers” by siril yella using supervised neural networks like MLP with back propagation, radial basis functions etc., which requires sample data for training the classifier at final classification stage(Christos, dimitrios siganos,2008),this research study is the background for this project work. The sample data collected in the past works were based on the impact acoustic analysis and image processing techniques and the features obtained by further processing of
the data are fused at different levels like sensor level, feature level and classifier level still where the classification of the wooden rail sleepers were based on judgments of sleeper inspector and is itself not accurate for good classification results.

In this thesis work an alternative is suggested to use, a non-supervised clustering method like self organizing map (SOM) which does not require data for training, rather the classification is done by features extracted from data. The data is collected by developing a machine vision system.
2 Background

2.1 Unsupervised neural networks

Neural networks when applied to many problem areas have given successful results. This is the main factor to use unsupervised artificial neural network (ANN) for this project work so that they can extract patterns and detect them which are too complex to be noticed by either humans or other computer techniques.

By definition, An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in union to solve specific problems. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process which is either supervised or unsupervised. (Michael A. Arbib, 2008)

One of the important applications of neural networks is pattern recognition. Pattern recognition by supervised learning means network is trained to associate outputs with input patterns. When the network is used, it identifies the input pattern and tries to output the associated output pattern. In the case when a pattern that has no output associated with it, is given as an input. The network gives the output that corresponds to a taught input pattern that is least different from the given pattern. (Michael A. Arbib, 2008) (Supervised neural networks, 2008)

Creating networks which find patterns in data sets without supervision is amazing as the impact of human error accuracy will be reduced, as unsupervised networks learn on their own in a kind of self study. A data set is presented to such networks and they learn to recognize patterns in the data set. That is, they categorize the input data into groups.
The network does not understand the meaning of the groups. The human user has to interpret or label the groups in some meaningful way. Depending upon the unsupervised classification results given by the neural network, the human user has to label them in to different groups.

2.1.1 Self organizing Map (SOM)

One of the most popular ANN is a self-organizing map (SOM) that is trained using unsupervised learning to produce a low-dimensional, discredited representation of the input space. SOM is based on unsupervised and competitive learning. In competitive learning networks like self-organizing map, all the neurons of the network receive the same input.

The input points that are near each other in the input space are mapped to nearby map units in the SOM. The cells have lateral competition and the one with most activity “wins”. Learning is based on the concept of winner neurons. The SOM can thus serve as a cluster analyzing tool of high-dimensional data. SOM give an idea of clustering means similar expression patterns. SOM not only separates the data into clusters but also determines its relatedness to other cluster.

Fig 2.1 A simple SOM

The data fed to a SOM includes all the information that a network gets. If erroneous data is fed to the SOM, the result is also erroneous or of bad quality. The teaching consists of choosing a winner unit by
the means of a similarity measure and updating the values of codebook vectors in the neighbourhood of the winner unit. (Wiki article, 2008), (Jeremy, 2009) (kohonens SOM)

2.2 Machine vision in railways

Acquiring the digital image of railway sleeper and the analyses based on that photograph do the same work that human inspection professionals does. The problem of testing sleepers, either wooden or concrete is a problem in every country, and the sleeper inspection is done by using automatic interpretation of NDT data. Machine vision requires digital input/output devices and a computer network to control other manufacturing equipment by this it replaces the manual visual inspection with an automatic inspection system.

The goal of the machine vision system in this project is to develop an inspection system for visual testing in order to be able to perform complete sleeper surface testing automatically. The methodology developed is applicable globally on all the wooden rail sleepers for defect detection. The goal of this methodology is to detect sleeper defects which can be seen by human eyes, but classify them in an efficient way. (Grossbergs, 2009)

Machine vision replaces human vision in that it attempts to interpret images. Human vision deals with the global information available in a scene, resolves ambiguities due to perspective, lighting, and attribute, and can perform guidance through unfamiliar territories. In fact, human vision process is prone to subjective considerations, fatigue, and boredom, which interfere with consistent evaluations. (Chirstoper, 2007),(McGraw-Hill,1995)(wiki article,2009)

Unlike human vision the sleeper images captured by machine consists of lot of details and they vary in size, like objects with different shapes, shadows can also be encountered, which is a difficult problem to solve. The work in this project is limited to rail sleepers as they have received relatively little attention compared to other area of rails. Better solutions within the area would also enhance the current state of
art technology in solving problems concerning rail inspection; as all the areas within the rail inspection domain would be studied to a reasonable extent.

2.3 Pattern recognition

Pattern recognition is a method intended to classify data based on either a priori knowledge or on statistical information extracted from the patterns. The patterns to be classified are usually groups of measurements or observations collected from the target material being used.

Prior knowledge of all the information related to the problem in present is needed for pattern recognition. A complete pattern recognition system consists of a sensor that gathers the observations to be classified, a feature extraction mechanism that computes numeric or symbolic information from the observations; and a classification scheme that does the actual classifying or describing observations, relying on the extracted features. (wiley, 2005)

In this project work, the crack properties are collected by feature extraction on the raw data collected from around 200 sleepers. Feature like crack lengths, width, number of cracks were extracted from the data acquired by the method. The features extracted were stored as separate feature vectors of each and feature vectors are classified finally into two different classes called ‘good’ and ‘bad’ i.e., 1, 0 respectively. This classification of feature vectors into good and bad classes is very useful during the further process of pattern classification.

As the relevant data needed for processing is extracted in the form of features, depending upon the choice of the human user developing the automated rail inspection system. Feature extraction was done by applying relevant image processing techniques on the data collected by machine vision.

The classification scheme is usually based on the availability of a set of patterns that have already been classified by feature extraction. This set of patterns is termed the training set and the resulting learning strategy can be supervised learning or unsupervised, in the sense that the system is not given an a priori
labelling of patterns, instead it establishes the classes itself based on the statistical regularities of the patterns. This helps in forwarding unnecessary data to the classifier. (B.Lerner 2009)(J.PMarques, 2001)

![Diagram of pattern recognition routine](image)

Fig.2.3 Diagram of pattern recognition routine

A wide range of algorithms can be applied for pattern recognition from supervised Bayesian classifiers to much more powerful unsupervised neural networks. In this project work non supervised learning SOM has been implemented for actual classification of wooden rail sleepers.
3 Machine vision system

3.1 Introduction

Image acquisition, is the process of gathering the data from images, which is essential for automating the visual inspection routine and is quite complex as the camera is placed on the target material to capture the images and if the camera is not properly placed the image acquisition process results in blurred images which gives faulty results in further processing with the data from the images. The design of the test vehicle with camera should give the better possibility to capture images.

There are different constraints that may arise while capturing images means the system or vehicle being considered for the process should be properly built to keep it within the load gauge limit, and focus of the camera should be able to provide complete details about the object from its image, and also lighting conditions in order to proceed further with the necessary experiments.

This procedure of capturing images is challenged by various atmospheric factors such as light and weather conditions. The advances in technology has made the present day cameras a more capable, compact and amazingly powerful than they were a few years ago. Image acquisition is becoming simple and able to maintain quality. For example, images concerning railway track profile, rail surface, railway sleepers, examining aircraft composites etc, demand different camera positions in each case. So, it should be realised that determining any standard approach of acquiring images is highly impossible.

There are a variety of trade-offs to consider in selecting a digital camera. One of the most sleepers were acquired by considering only the image part from the rail to its outer edges on either side of the sleepers (Siril Y, 2007). The data was collected from approximately 200 rail sleepers.
3.2 Experimental setup

In this project work the test vehicle was setup with a Nikon D70 camera mounted on the vehicle which can roll over the rails at a fixed length and proper angle is maintained through the entire process of image acquisition. This digital camera captured images in various resolutions. The camera is fixed to the vehicle running over the rails and the image of each sleeper is captured in turn with the images being stored temporarily within the camera itself.

This experimental setup is run over the rail tracks and image of each and every sleeper is captured by positioning the camera in two different views, top and horizontal view of the sleepers. This is in order to capture the wooden railway sleepers from the rail to its outer edge since most of the necessary information which really affects the condition of the sleeper is available in this region of the sleeper. Using this image acquisition procedure a total of 800 real images of the wooden railway sleepers of either side edges have been acquired for its process of image analysis in order to extract the required features available from those images. After image acquisition, those images have been transferred to the computer and image analysis is carried out applying the image processing techniques for analysing and calculating those image features. (Siril.Y, 2007)
During image acquisition process the images of the wooden railway sleepers were acquired by considering only the image part from the rail to its outer edges on either side of the sleepers (Siril Y, 2007). Totally, the number of images collected were 800; with 400 images on the left side where 200 images are showing the wooden part of the sleeper (see Figure 2.1) and 200 images are showing the metal plate and nail(s) used for fastening the rails (see Figure 2.2), and 400 images on the right side of the same sleeper with images on its right side; out of which 200 images are showing the wooden part of the sleeper (see Figure 2.3) and 200 images are showing the metal plate and nail(s) used for fastening the rails (see Figure 2.4). Since this is the part of the sleeper which a human inspector also considers for the manual checking of the sleeper condition. The figures below depict the camera view used in capturing the wooden railway sleepers in both good and bad conditions respectively.(Siril Y, 2007)(Siril Y, 2009)

![Fig.3.2 Sleeper image](image1)
![Fig.3.3 plate image](image2)
3.3 Pre-processing for feature extraction

In this work the raw data collected in the form of images by the test vehicle are loaded to the computer and further processed to transform the input data into the sets of features as the features set will extract the relevant information from the input data in order to perform the desired task. The feature set selection depends upon the choice of the user. (wiki article, 2009) A total of 800 images i.e. 200 images of left and right side of sleeper each and 200 images of the metal plate on each side were acquired. The images size captured by test vehicle is not supportive for computational purpose, so they were resized to 200x300 pixels.

The four features considered to extract are number of cracks, length of the crack, and width of the crack and length of the metal plate were stored in separate feature vectors. These feature vectors are finally classified into two different classes called ‘good’ and ‘bad’ i.e., 1 and 0 respectively. Further processing of sleeper images was done by the relevant image processing techniques in Mat lab. The procedure is as, (Siril Y, 2009)

Stage-1

The colour images were converted to gray scale to eliminate the unnecessary details.

Stage-2

The images were blurred using Gaussian low pass filter to eliminate unnecessary contents in the image like stones and to reduce the noise.

Stage-3

As the contents in the sleeper image are to be discriminated for the purpose of eliminating the unnecessary components and considering the needed ones, an entropy filter of 11x11 size was applied on to the images as,

\[
\text{Entropy} = -\sum_i \sum_j P[i,j] \log P[i,j]
\]
Stage-4
The output images of the entropy filter were converted to binary or bi-level images that have only two values for each pixel either black or white. The purpose of this conversion is to remove any remaining unnecessary contents in the image. The components of the images which have a gray threshold value of less than 0.65 are eliminated.

Stage-5
The morphological image processing operations like majority and dilation were applied for the final removal of unnecessary components. Due the dilation operation the adjacent black pixel to a white pixel is changes into a white pixel and this improves the contrast of the image.
By the 3- by-3 neighbourhood of the pixels, the majority operation sets the pixel values to ‘1’ if the adjacent pixels are ‘1’ s. By the morphological operations the crack pixels are indentified.

Stage-6
By identifying the crack pixels the there can be a misconception in computing the number of cracks, as due to the presence of any stone on the crack makes one single crack separated to two loosing the integrity of the crack. To overcome this problem the cracks were joined by a straight line, if the distance between them is less than or equal to 35 pixels.

Stage-7
The skeleton operation of morphological processing is used from where the skeleton of the image shape is obtained. Skeleton of the crack image is like a line which is one pixel wide and one-pixel thick. The skeleton image is further pruned to eliminate the unwanted spurs which impacts length calculation.

(Siril Y, 2007)
From these resulted pre-processed images the calculation of features such as number of cracks, length of crack, width of crack and the condition of metal plate was determined. The different classes of wooden sleepers categorized by the image acquisition method (see fig.3.4)

![Possible sleeper conditions diagram](image)

Fig.3.4 Different classes of sleeper conditions
4 Features extracted

4.1 Introduction

The visual inspection of material is being carried in all sectors of transportation business and railways are not an exception to ensure the quality of the service they provide by regular check and maintenance. Usually the visual inspection in railways is done by human who is trained in the specific procedure. But as time goes on the need for fast and efficient maintenance is required that lead to the commencement of automation of the inspection systems. One of the condition monitoring sectors that needed the automation of visual inspection system is the rail sleepers. In most of the countries the sleepers are made of wood due to economic factor. (Wiki article, 2009)

In the current work the wooden sleepers from different atmospheric conditions were taken to conduct experiments, i.e. to collect data and process the data for condition monitoring of the sleepers. As all the transportation areas demand reliable, accurate and fast solutions in order to avoid catastrophic results. Machine vision approach is applied in various fields of transport; such as road, aerial, water and rail transport areas.

Many technologies have emerged and the recent advances in this area are, a company MER MEC has designed a vision based system ‘track surface defect detection’ for online track condition monitoring, another company has developed a vision based system for condition monitoring of concrete sleepers and ballast less track surface conditions.

In the current work the manual condition monitoring of wooden sleepers is automated by NDT machine vision. In manual inspection the human operator observes each and every sleeper and analysis the condition of the sleeper, i.e. by the number of cracks on the sleeper according to the intuitive skills he owns.
The manual inspection procedure is replicated by capturing the sleeper images and acquires data from the images and then applying relevant image processing techniques to get the feature which make the final classification of the sleeper images as good or bad. (B.Lerner 2009)(J.PMarques, 2001)(Siril Y, 2007)

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Table 4.1 Data collected by test vehicle

4.1.1 Number of cracks
For finding the numbers of cracks first the images were labelled based on the pixel connection. The labelling was done by 4-connected components. The pixel labelled ‘0’ means background, pixel labelled ‘1’ means one crack, pixel labelled ‘2’ means two cracks.

4.1.2 Length of the crack
After finding the number of cracks, the length of each crack is determined. The image of wooden sleeper may consist of many numbers of cracks, but the one with largest length is considered. The length of the crack is calculated as the distance between the white pixels on a crack skeleton. The starting point i.e. first white pixel encountered is taken as ‘x’ and the checking is done until last white pixel on that crack skeleton is reached. This particular approach is easy to use and works uniformly on all.

4.1.3 Width of the crack
The crack with largest length is considered as second feature. The width of that particular crack is calculated as the third feature. The area of the crack selection was calculated by the ‘region props’
function from Mat lab toolbox. The area of the crack divided by the length of the corresponding crack gives the width of that particular crack.

4.1.4 Length of the metal plate

The level of the metal plate also determines the condition of wooden sleeper. So it is also considered as a feature. The metal plate and a nail hold the sleeper and the load from the rail are transmitted through the plate onto the sleeper.

As the time goes on the natural material like wood is impacted by the usage, load and the environment, it compresses and sinks down. Edge detection is mostly used for segmenting images based on abrupt changes in intensity. Further canny edge detection operator was used to find the edges of the plate nail and rail in the image. As a result the unnecessary details in the image were removed. The skeleton of that image is taken and pruned for unnecessary urging. The length of that image skeleton is found similarly as length of the plate. If the length of the metal plate and that of the skeleton image is same, then the metal plate is not sunk. If the difference in the length is more, then the metal plate is sunk. (Siril Y 2007)
Fig. 4.2 various stages of processing on a Case-1 sleeper

(a) Original image. (b) Gaussian low pass filtered image. (c) Result of applying “11 x 11” entropy filter (d) Binary image obtained by thresholding the texture image (e) Removing irrelevant small objects and performing dilation (f) Majority operation followed by joining nearby pixels to ensure crack continuity (g) Separation of crack. (h) Skeletonised image. (i) Result of pruning the skeletonised image
Fig. 4.3 various stages of processing on a Case-2 sleeper

(a) Original image. (b) Gaussian low pass filtered image. (c) Result of applying “11×11” entropy filter. (d) Binary image obtained by thresholding the texture image. (e) Removing irrelevant small objects and performing dilation. (f) Majority operation followed by joining nearby pixels to ensure crack continuity. (g) Separation of crack. (h) Skeletonised image. (i) Result of pruning the skeletonised image.
Fig. 4.4 various stages of processing on a Case-3 sleeper

(a) Original image. (b) Gaussian low pass filtered image. (c) Result of applying “11×11” entropy filter (d) Binary image obtained by thresholding the texture image (e) Removing irrelevant small objects and performing dilation (f) Majority operation followed by joining nearby pixels to ensure crack continuity (g) Separation of crack. (h) Skeletonised image. (i) Result of pruning the skeletonised image

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Fig. 4.5 various stages of processing on a Case-4 sleeper

(a) Original image. (b) Gaussian low pass filtered image. (c) Result of applying “11×11” entropy filter. (d) Binary image obtained by thresholding the texture image. (e) Removing irrelevant small objects and performing dilation. (f) Majority operation followed by joining nearby pixels to ensure crack continuity. (g) Separation of crack. (h) Skeletonised image. (i) Result of pruning the skeletonised image.
4.2 Determining the condition of the metal plate

The wooden rail sleeper is fitted with the metal plate and nails and the material like wood gradually loses its quality and shape due to weather conditions and also of the load and duration of its usage. This causes the metal plate to sink and is the main cause considered in the manual inspection of the sleeper condition. So the condition of the metal plate ultimately indicates the condition of the rail sleeper.

Once the plate images were collected they are converted to gray scale and unnecessary contents were removed by applying Gaussian low pass filter. Using canny edge detection operator the edges of plate, nail and rail are detected. The resultant image was dilated and the skeleton of the image was calculated and pruned to remove unnecessary contents. The length of the metal plate was found from the skeleton of the image. If the length of the original metal plate image is ‘n’ pixels and the length of the skeleton of the image is ‘n’ pixels, i.e. if both the lengths are same the plate is not sunken. If the length of the skeleton of the image is around ‘n/2’ the plate is partially sunken or if length is very low than ‘n/2’ then the plate is fully sunken. (Wiki article, 2007). The condition of the metal plate affects the condition of the rail sleeper, it is also considered as one of the feature.
Fig. 4.6 various stages of processing on a Case-1 plate

(a) Original image  (b) Gaussian low pass filtered image  (c) Result of canny edge detection  (d) Dilation  (e) Skeletonised image  (f) Result of pruning the skeletonised image
Fig. 4.7 various stages of processing on a Case-2 plate

(a) Original image (b) Gaussian low pass filtered image (c) Result of canny edge detection (d) Dilation (e) Skeletonised image (f) Result of pruning the skeletonised image
Fig. 4.8 various stages of processing on a Case-3 plate

(a) Original image  (b) Gaussian low pass filtered image  (c) Result of canny edge detection  (d) Dilation  
(e) Skeletonised image  (f) Result of pruning the skeletonised image
Fig. 4.9 various stages of processing on a Case-4 plate

(a) Original image  (b) Gaussian low pass filtered image  (c) Result of canny edge detection  (d) Dilation  
(e) Skeletonised image  (f) Result of pruning the skeletonised image
4.3 SOM as classifier

Based on the features extracted in the previous stages of image processing techniques the initial classification was obtained using self-organising map. The datasets were given as training sets obtained from left and right sets of sleeper images. Linear initialization along two greatest eigenvectors is used after initialization; the SOM is trained in two phases: first rough training and then fine-tuning. If the 'tracking' argument is greater than zero, the average quantization error and topographic error of the final map are calculated. Euclidean metric was used in SOM algorithm to measure distance between vectors and all the normalisation was single variable i.e. using one kind of normalisation to one variable. The initialisation was by linear and the training was done using batch algorithm. The U-Matrix was calculated on all the variables i.e. distance between the neighbouring map units. The U-matrix and feature vectors i.e. the input samples to the SOM were arranged as in the below figures. The feature vectors were initially classified into two clusters and some isolated data in between.

Fig.4.10 SOM visualisation of left side sleeper images in MATLAB
The SOM allows us to see similar entities placed in the same map unit or adjacent map units. However, if the samples are not similar, the distance between the corresponding map units is shown on the U-matrix display with warm (red, yellow) colors. The automate clustering was done using K-Means clustering.

### 4.3.1 Classification results obtained by Self organizing map

<table>
<thead>
<tr>
<th>Pattern classifier</th>
<th>Class</th>
<th>Patterns</th>
<th>Number of errors</th>
<th>% Correct Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOM</td>
<td>Bad (0)</td>
<td>14</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Good (1)</td>
<td>36</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Overall</td>
<td>50</td>
<td>12</td>
<td>82</td>
</tr>
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</table>

Table 4.3.1 Results showing the classification from the features of sleeper left side images
The overall classification using the self-organising map as a classifier resulted with 84% classification accuracy. The erroneous data from the images of the sleeper could be that a part of the sleeper is missing and images possessing numerous cracks, but the cracks are fairly small that lead to the 10% error on the aggregate. The performance can be achieved by applying the data fusion methodology at different levels.

<table>
<thead>
<tr>
<th>Pattern classifier</th>
<th>Class</th>
<th>Patterns</th>
<th>Number of errors</th>
<th>% Correct Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOM</td>
<td>Bad (0)</td>
<td>14</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Good (1)</td>
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<td>0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Overall</td>
<td>50</td>
<td>7</td>
<td>86</td>
</tr>
</tbody>
</table>

Results showing the classification from the features of sleeper right side images
5 Data Fusion

5.1 Introduction

By Data fusion different sources of information are combined to improve the performance of a method or system. The fusion of data is done in the case of using various sensors typically to detect a target material through the pre collected images. The different sources of inputs may originate from a single sensor at different times or even from different sensors at a given time. Such fusion of data seems to be worth applying in terms of uncertainty reduction. Each of individual methods produces some errors, and assuming that all individual methods perform well, combination of such multiple experts should reduce overall classification error and as a consequence emphasize correct outputs. (Wiki article, 2007) Fusion may be useful for several objectives such as detection, recognition, identification, tracking, change detection, decision making, etc. These objectives may be encountered in many application domains as Defence, Robotics, Medicine, Space, etc.

Fusion process is categorized as low, intermediate and high level fusion depending on the processing stage at which fusion takes place. Low level fusion combines several sources of raw data to produce new raw data, Intermediate level fusion combines various features such as edges, corners, lines, texture parameters, etc are combined into a feature map that may then be used by further process. High level combines decisions coming from several methods or levels of fusion. In the current work the three levels of data fusion was achieved at sensor-level, feature-level, classifier-level. For this work fusion of data is suggested to achieve better results in condition monitoring of the sleeper.

The reliability of the results depends upon the size of the available database and the amount of expert knowledge available and also on the validity of that knowledge. The data collected from the NDT method machine vision were fused in this work. (Siril Y, 2009)
5.2 Sensor-level fusion

Sensor fusion is the low level fusion process of combining data derived from various sensors. The sensor fusion can also be done by combining the data collected by a sensor at different moments. Sensor fusion can be implemented by methods and algorithms like Kalman filter, Bayesian networks, Dempster-Shafer. In the current work the data collected by different sensors through machine vision were fused. The combination of data from different sensors is to acquire accuracy in condition monitoring of sleeper.

In the current work in this fusion level, since the data is fused in non compressed form means both relevant and irrelevant data makes a large data set so the fusion at sensor level does not give the expected results and hence further processing at feature extraction and pattern classification became a huge task then. (Siril Y, 2009)

![Diagram of sensor level fusion](image_url)

Fig.5.2 Diagram of sensor level fusion
5.3 Feature level fusion

Feature fusion is the intermediate level fusion process of combining different feature sets collected from raw data. In this work the feature sets of either sides of the rail sleeper were fused. Initially the data collected by sensors in each method of left and right ends of the sleeper are processed and features were extracted. The extracted features were separated into feature vectors each. The feature vectors extracted from the left end data of the sleeper were fused with that of those extracted from the right end data of the sleeper.

![Feature level fusion diagram](image)

**Fig.5.3 Diagram of feature –level fusion**

5.3.1 Classification Results of feature level fusion

<table>
<thead>
<tr>
<th>Pattern classifier</th>
<th>Class</th>
<th>Patterns</th>
<th>Number of errors</th>
<th>% Correct Classification</th>
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</thead>
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<td>Good (1)</td>
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<tr>
<td></td>
<td>Overall</td>
<td>50</td>
<td>9</td>
<td>82</td>
</tr>
</tbody>
</table>

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5.4 Classification results of unsupervised versus supervised from past works

For applications where prediction is required, and where accuracy is more important, supervised method is useful. A research work was done by ‘Siril Yella: Pattern Recognition for Automating Condition Monitoring of Wooden Railway Sleepers’ to automate the visual inspection of the rail sleepers using supervised learning techniques of neural networks. The current thesis work is motivated by the methodology developed for data collection till feature extraction and further processing of the data. The pattern classifiers used were MLP, GMM, SVM etc. The existing methods for dealing with this problem can at best solved the classification problem with 86 to 90 percent correct classification. In the current thesis work using unsupervised pattern classifier SOM, the correct classification was 82 to 86 percent. The classification results from the existing research work:

<table>
<thead>
<tr>
<th>Supervised Pattern classifiers</th>
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<th>% Correct Classification</th>
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</thead>
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<td>3</td>
<td>90</td>
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<tr>
<td></td>
<td>Good (1)</td>
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<tr>
<td></td>
<td>Overall</td>
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<td>5</td>
<td></td>
</tr>
<tr>
<td>GMM</td>
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<td>5</td>
<td>88</td>
</tr>
<tr>
<td></td>
<td>Good (1)</td>
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<tr>
<td></td>
<td>Overall</td>
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</tr>
<tr>
<td>SVM</td>
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<td>90</td>
</tr>
<tr>
<td></td>
<td>Good (1)</td>
<td>36</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Overall</td>
<td>50</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>
Classification results of the current thesis work:

<table>
<thead>
<tr>
<th>Unsupervised Pattern classifier</th>
<th>Class</th>
<th>Patterns</th>
<th>Number of errors</th>
<th>% Correct Classification</th>
</tr>
</thead>
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<td>SOM</td>
<td>Bad (0)</td>
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<td>4</td>
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</tr>
<tr>
<td></td>
<td>Good (1)</td>
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<tr>
<td></td>
<td>Overall</td>
<td>50</td>
<td>5</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Class</th>
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<tbody>
<tr>
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<td>86</td>
</tr>
<tr>
<td>Good (1)</td>
<td>36</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>50</td>
<td>7</td>
<td></td>
</tr>
</tbody>
</table>

In supervised pattern recognition system a set of patterns is known initially and the learning method is generally decided as per application data is available where as a typical SOM is made of a vector of nodes for the Input, an array of nodes as the Output map, and a matrix of connections between each Output unit and all the Input units. Thus each vector of the Input dimension can be mapped to a specific unit on a two-dimensional map. In the current thesis work each vector represents a feature, while the output unit represent the category that the feature is assigned to. Supervised competitive ANN like MLP, RBFNN etc which also transforms high dimensional data to a two dimensional grid, without regarding data topology. It uses pre-assigned cluster labels to data items; to facilitate the two dimensional transformation minimizing the average expected misclassification probability. Unlike SOM, where clusters are generated automatically based on items similarity, here the clusters are predefined.
Considering the results, it looks like supervised learning yields better results when used with small training set than the unsupervised learning. However, as the size of the training set grows, the advantage of the supervised learning may disappear. The former finding is leading to the initial conclusion that given enough training examples, automatic classification gets close to user subjective classification.

Both methods yielded about 87% of overall success in categorizing the rail sleepers. In order to evaluate more accurately the performance of both methods, a more thorough analysis is needed. Besides the overall categorization success there is a need to evaluate each cluster separately, for precision and recall of specific clusters. The influence of the size of various clusters needs to be looked at. The size of the training set needs also to be better understood.

The classification results of feature level fusion shows that existing method and that of the current thesis work are similar. The feature level fusion results can be considered good as they solve the human prone error accuracy problem.
6 Conclusion

In this project work a system is developed to automatically test the condition of the wooden rail sleeper. A test vehicle is designed for this process to achieve the desired results of condition monitoring. The system is moved manually along the rail tracks and it detects the condition of the wooden railway sleepers by capturing the images of the sleepers and processing the images acquired. The purpose of rail condition whether by manual inspection or automated monitoring is to ensure the security of the rail property and safety to the users by avoiding rail accidents causing injury or death of passengers and also reducing the material damage to the railways. But the automatic condition monitoring is to identify the faults in sleepers in less time and in reliable and robust way.

The traditional approach of rail inspection for over several years associated with the rail infrastructure, is that a human operator moves along the track and by the visibility and sound analysis techniques on the wooden sleeper decide the condition of the sleeper, but it was heavily involved with the human intervention which is prone to fatigue due to human errors. To avoid these human errors and also to improve the speed of the process with robustness and reliability ensuring safety and security within time, a reliable machine is required and this has lead to the development of a machine vision system.

In the project the wooden rail sleepers were considered as a case because railways from many years are using wood material for sleepers and the sleeper condition is considered as the one that plays a role mostly in any rail accidents. The experimental setup to avoid damages should not cause damage so NDT methodology which causes no damage to the material being inspected is developed.

From wooden sleepers data is collected in the form of real onsite images and they are processed using various image processing techniques like image acquisition, in the initial stage with images captured in two different views; one image having the wooden sleeper part for identifying the cracks and another image having the metal plate part for identifying the rail fastenings. From the rail fastening image part it is easy to find the availability of the fastenings.
The image part of the rail fastening is used to find whether the metal plate used for fastening is sunken into the wooden sleeper or not which determines its condition as good when it is not sunken and as bad if it is sunken.

The data collected from sleepers for automatic condition monitoring involves extraction of necessary features and elimination of unnecessary features from the collected images. In this project work the features extracted from sleeper images were number of cracks, length of the crack, width of the crack, and length of the metal plate. The lengths or widths with maximum values are extracted as they are the real cause and visually appeal wooden sleeper condition. The extracted features were stored in feature vectors for their classification using pattern recognition classification task.

Self organising map(SOM) is used as classifier for classifying the wooden sleeper into two classes of ‘good’ and ‘bad’ depending on the condition of wood. This NDT approach of data collection could be unreliable if there are false positive values of the patterns classified (mentioned in the fig.3.4). The desired results of classification of sleepers as ‘good’ or ‘bad’ depends on the test vehicle and camera positions for image acquisition, vehicle dynamics, and vehicle speed and camera response should be considered. Issues concerning image analysis, feature extraction and classification should also be embedded into the vehicle for automation.

At the final stage of processing the fusion was used on the sensor level data and feature level data. And this current machine vision approach could be further extended to fusion analysis by using sound analysis techniques that could easily detect the condition of the fastenings that is, with the rattling sounds produced from the wooden railway sleepers when they are struck hard with some material or object. Thus sound analysis will detect the condition of the rail fastenings and helps in the automation of machine vision process of condition monitoring.
This approach was not capable enough to detect the condition of the rail fastenings and to solve such problems with different technique in order to identify the material condition. The current system may be able to be helpful to use with a different experimental setup and with a different approach to extract features from the raw information on sleepers made of different materials other than wood.

Further work in automatic condition monitoring can be aimed by automating the whole experimental setup means acquiring the images automatically, while the vehicle is running on the tracks. For such a setup to become reality several key issues such as vehicle and camera positions for image acquisition, vehicle dynamics, vehicle speed and camera response should be considered. Issues concerning image analysis, feature extraction and classification should also be embedded into the vehicle for automation. Since certain specific situations where the method fails have been identified, further development of the technique can hopefully improve performance still further.
7 References


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