WAVELET PACKET BASED DETECTION OF SURFACE FAULTS ON COMPACT DISCS

Peter Fogh Odgaard * **Jakob Stoustrup** *
Mladen Victor Wickerhauser **

* *Department of Control Engineering, Aalborg University, Fredrik Bajers Vej 7C, DK-9220 Aalborg, Denmark, odgaard@control.aau.dk*
** *Department of Mathematics, Washington University, One Brookings Drive, St. Louis, MO 63130, USA, victor@math.wustl.edu*

Abstract
In this paper the detection of faults on the surface of a compact disc is addressed. Surface faults like scratches and fingerprints disturb the on-line measurement of the pick-up position relative to the track. This is critical since the pick-up is focused on and tracked at the information track based on these measurements. A precise detection of the surface fault is a prerequisite to a correct handling of the faults in order to protect the pick-up of the compact disc player from audible track losses. The actual fault handling which is addressed in other publications can be carried out by the use of dedicated filters adapted to remove the faults from the measurements. In this paper detection using wavelet packet filters is demonstrated. The filters are designed using the joint best basis method. Detection using these filters shows a distinct improvement compared to detection using ordinary threshold methods.

Keywords: Fault Detection, CD ROM, Fault-Tolerant Systems, Time-Frequency Localization, Signal Analysis

1. INTRODUCTION

Optical disk players have problems playing disks with surface faults such as scratches and fingerprints. In this work Compact Discs (CD) are only considered since these are practically more simple to deal with than the DVDs and Blue-Ray disks. However, transparency among the different types of optical disks can be assumed, meaning that work on handling surface faults on CDs is extremely relevant for the handling of surface faults on DVDs and Blue-Ray disks as well. The underlying problem is to be found in two servo control loops in the CD-player. In the CD-player the optical pick-up does not have any physical contact with the track in which the data is stored. It is, however, highly important that the laser beam emitted from the optical pick-up is focused and positioned on the information track, see Fig. 1, if this is not the case the CD-player will not be able to retrieved the stored data. The laser beam is focused and tracked by the usage of two servo control loops. The controllers in these two servo loops are fed with position sensor signals generated by the optical pick-up unit. During a surface fault these position signals contain a component due to the fault as well as the normal position. Unfortunately, the frequency content of these fault components is in a frequency region where high controller sensitivity is required. This makes it a conflicting problem to handle both disturbances and surface faults with the same linear controller. This control problem is instead often solved by the use of a fault tolerant control scheme. The short version of this scheme is as follow. The occurrence of the surface fault is first detected. This detection triggers a scheme of special actions which accommodates the given fault.

In (Odgaard 2004) and (Odgaard *et al.* 2006*b*) this control problem is suggested to be solved by a scheme called feature based control. It handles the fault by the following: Detect the surface fault, and when the fault is detected the fault components in the measurement signals can be removed by the use of filters adapted to remove the surface faults. Since the fault components have been removed from the position measurements the standard controllers can be used to position the optical pick-up.

In order to remove the fault component entirely from the measurements it is clear that it is important to have a good precise detection of the surface faults. Practical experiences have shown that even an improvement of only a few samples can be very important. An improved fault detection scheme is also usable for other schemes handling the surface faults, as long they are based on a detection of the surface faults.

Results from (Schneiders 2001) and (Goossens and Odgaard 2003) indicate that the use of wavelet and wavelet packet bases for localization of faults in time are advantageous. I.e. the use of a joint time and frequency domain, such as the wavelet or wavelet packet basis, improves the detection of the surface faults. In (Schneiders 2001) wavelets are used to detect the surface faults on CDs. A wavelet packet based method is used for fault detection in a DVD-player, which is a different but strongly related optical disk player. This fault detection is a part of a method to handle surface faults, see (Goossens and Odgaard 2003).

Subsequently only one type of surface faults are considered. It is scratches, since these together with fingerprints are the most often occurring faults, and fingerprints can be represented by a number of small scratches. Even though only scratches is considered in this work. This type of surface faults is such a large class, that a filter designed to detect one scratch can not be assumed to detect all. The wavelet and wavelet packet filters designed in (Schneiders 2001) and (Goossens and Odgaard 2003) are based on only one training signal, meaning only one scratch. Consequently this filter might not detect other scratches as well. Meaning these filters are not robust towards other scratches than the one it is designed to detect.

This over-training to the scratches in the training set results in wavelet filters which have a too narrow-pass band, meaning that the main energy of the other scratches is outside the pass band of the designed wavelet filters. This is more or less the same conclusion obtained in (Ye *et al.* 2004), where it is concluded that a too narrow-banded filter used for fault detection results in a clear increase in the the number of non-detected faults.

This problem of designing a wavelet packet filter to detect surface faults which are not entirely alike, can be handled better using the joint best basis search, instead of the best basis search, which only finds the best basis given one signal and not a set of signals. The joint best basis method depends on an information cost function. In practice it has been very difficult to find one usable cost function in this application. Instead the joint best basis algorithm is changed in a more practical direction.

In this paper the experimental setup is described first together with training and test data. It is followed by a description of the wavelet packet basis, best basis search method and joint best basis based method. This method leads to some experimental results on the training and test data. A conclusion is given in the end of the paper.

2. EXPERIMENTAL SETUP AND PRACTICAL CONSIDERATIONS AND TRAINING DATA

The experimental setup consists of a CD-player, with a three beam single Foucault detector principle, a PC with an I/O-card, and some hardware in order to connect the CD-player with the I/O-card. Due to the limited computational power of the CPU in the PC the sample frequency is chosen to 35 kHz. This is lower than the normal CD-servo sample frequency (44 kHz). The optical pick-up in the CD-player can be positioned in two directions called focus and radial, see Fig. 1. These movements are controlled in the way that the focus and radial distances, (e_{f} and e_{r}), are minimized.

The four photo detector signals are measured. From these measurements two difference signals have been calculated as described in (Odgaard *et al.* 2006*a*). One difference signal represents a change in gain to the two photo diodes measuring deviation in the focus position. The other difference signal equivalent represents a change in gain in the radial position.

From these both differences, the focus and radial distances can be estimated, see (Bouwhuis *et al.* 1985). The distances are illustrated in Fig. 1. The pairwise sums of the these detector signals are often used as residuals for detection of surface

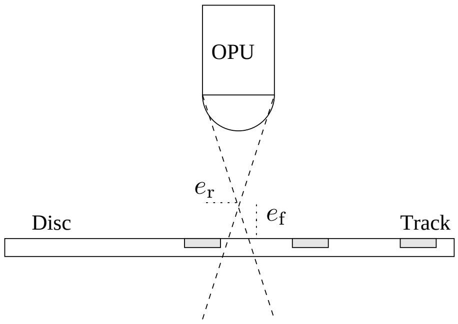

Figure 1. The focus distance, e_f, is the distance from the focus point of the laser beam to the reflection layer of the disc, the radial distance, e_r, is the distance from the center of the laser beam to the center of the track.

faults, since the sums of the signal pairs depend on the total reflected laser energy (focus sum: α_f, and radial sum: α_r). A surface fault changes the structure of the disc surface and thereby changes the path of the laser beam. I.e. a larger part of the laser will not be reflected back at the detectors in the optical pick-up. However, these residuals are not totally independent of the pick-up position. In this paper the signals are preprocessed in order to calculate residuals which are better decoupled from the pick-up position, see (Odgaard *et al.* 2006*a*).

If the sums are taken of the respective pairs of detector signals a focus fault residual, α_f, and a radial fault residual, α_r are computed.

2.1 Training data

From the focus and radial residuals, $\alpha_\mathrm{f}[n]$ and $\alpha_\mathrm{r}[n]$, faults are extracted based on the algorithm described in (Odgaard and Wickerhauser 2004). From a large number of CDs, with scratches, sequences with detected scratches are extracted into a column vector with the length of $256=2^8$ samples. This length is chosen since all scratches in the data set are shorter than 256 samples. The scratches are extracted with symmetric geometric center intended to be in the middle of the fault vector.

This extraction gives two matrices with faults. The faults in $\alpha_\mathrm{f}[n]$ are collected in $\mathbf{F}_\mathrm{f}$ and the faults in $\alpha_\mathrm{r}[n]$ are collected in $\mathbf{F}_\mathrm{r}$, where each column in the matrices is a fault vector. In addition four other scratches are forming a test set. This set is used for testing the design detection algorithm.

3. WAVELET PACKET BASIS, BEST BASIS AND JOINT BEST BASIS

It is difficult to separate the surface faults from the disturbances in time or frequencies only. I.e. it might be useful to use a joint time and frequency methods. The wavelet packet transform is such a joint time and frequency transform. A wavelet packet transform might be used to separate the surface faults from the disturbances, and thereby detect the surface faults. This wavelet packet transform is done by a basis shift from the standard time basis to the best wavelet packet basis. This basis is the best wavelet packet basis given certain requirements. The wavelet package basis as well as the best basis and the joint best basis methods are shortly introduced. For more details see (Mallat 1999) and (Wickerhauser 1994).

3.1 Wavelet packet basis

The wavelet packet transform is formed by a number of wavelet transforms. The wavelet transform separates a signal space S_i into an approximation space S_{i+1} and a detail space D_{i+1} by dividing the original basis $(\Psi_i(t-2^i n))_{n\in N}$ into two new orthogonal bases

$$(\Psi_{i+1}(t-2^{i+1}n))_{n\in N} \text{ of } S_{i+1}, \tag{1}$$
$$(\Phi_{i+1}(t-2^{i+1}n))_{n\in N} \text{ of } D_{i+1}, \tag{2}$$

where N is a set of integers, and Ψ and Φ are respectively the wavelet function and its related scaling function. This decomposition is called the wavelet decomposition. The wavelet packet decomposition is formed if the approximation and details are decomposed once more, such that a tree structure is formed.

The discrete wavelet decomposition can be performed by the use of two filters: h, a low-pass filter and, g, a high-pass filter. The subspaces, also called atoms, in the wavelet packet tree can be indexed by depth, i, and the number of subspaces, p. This means that a decomposition at the parent node (i,p) can be written as

$$s_{i+1}^{2p} =< h, s_i^p >, \tag{3}$$
$$s_{i+1}^{2p+1} =< g, s_i^p > . \tag{4}$$

Notice the down sampling of the signal, which provides that the number elements in each decomposition levels do not increase. This important in order to preserve orthogonality of the basis.

It is possible to continue this decomposition as long that the s_i^p has the length of at least 2. However, it is clear that, it is possible to stop the decomposition of the tree at an earlier level and also at different depths in different parts of the tree. The final decomposition depths represent the wavelet packet basis. The question is how to find the best basis.

3.2 Best basis

A full wavelet packet tree contains a large number of possible bases. This number obviously depends on the depth of the tree. It can be computed recursively by: $N_0 = 1$ and $N_{L+1} = 1 + N_L^2$.

This clearly results in a fast decreasing number of possible bases depending on the numbers of levels in the tree, e.g. for a tree with 6 levels it is 458330 and with 7 levels $2.10 \cdot 10^{11}$.

A fast method for finding the best basis is as a consequence highly required. A fast method called the best basis search is derived in (Coifman and Wickerhauser 1992). In order to measure how suitable the basis is, an information cost function is introduced. The cost function measures the cost of a given representation, where the best basis has the smallest cost. Some of the commonly used information cost functions are: Number of elements above a given threshold, Concentration in l^p, Entropy, and Logarithm of energy.

Having the information cost function in mind, it is possible to describe the best basis search, (Wickerhauser 1994).

(1) Compute the cost function of all elements in the wavelet packet tree
(2) Mark all elements on the bottom level J
(3) Let $j = J$
(4) Let $k = 0$
(5) Compare the cost value v_1 of element k, (counting from the left), on level $j-1$ to the sum v_2 of the cost values of the elements $2k$ and $2k+1$ on level j.
    (a) If $v_1 \leq v_2$, all the marks below element k on level $j-1$ is removed, and element k is marked.
    (b) If $v_1 > v_2$, the cost value v_1 of element k is replaced with v_2.
(6) $k = k+1$. If there are more elements on level j(if $k < 2^{j-1} - 1$), jump to step 5.
(7) $j = j+1$. If $j > 1$, jump to step 4.
(8) The marked basis has the lowest possible cost value. This value is found at the top element.

One should notice that this best basis is found for only one signal. In this case this would imply that the best basis is found based on one scratch.

3.3 Joint best basis

The joint best basis is a method which takes the entire data set into account in finding the best wavelet packet basis. The joint best basis search finds the best basis given a set of signals, of the same length. It could be a number of signals with encounters of the same or different scratch(es). The joint best basis algorithm computes the jointly best bases given: the set of signals, an information cost function and a wavelet basis, see (Wickerhauser 1994) and (Coifman and Wickerhauser 1992). The algorithm is as follows:

(1) Compute the full wavelet packet tree of all the signals in the signal set.
(2) Compute the tree of means, by computing the mean of all signal trees at each position in the tree.
(3) Compute the tree of squares, by computing the sum of squares of all signal trees at each position in the tree.
(4) Subtract the tree of means from the tree of squares, to obtain the tree of variances.
(5) Find the best basis of the tree of variance by using the best basis algorithm, given an information cost function and wavelets.

A joint best basis is following found for $\mathbf{F}_{\mathrm{f}}$ and $\mathbf{F}_{\mathrm{r}}$, where some different wavelets and information cost functions were tried. The Daubechies 1-6 filters, see (Mallat 1999), were tried, since their filter taps look like a surface fault, together with the l^2 and Shannon information cost functions, see (Mallat 1999), all the combinations of these bases and cost functions were tried with poor results.

The problem in using the joint best basis algorithm directly is the choice of information cost function and the best basis search. Then used to fault detection, the scope is to find a band-pass filter which separates the surface fault from the background noises in the residuals. In other words the wavelet packet analysis is used to analyze the data in order to design a FIR-filter which is given by the wavelet packet level in which the fault is separated from the disturbances.

Instead of using a cost function, a heuristic based method is used. The method takes its starting point in the tree of variances, used in the joint best basis algorithm. The used method consists of the following steps:

(1) Compute the tree of variances, use step 1-4 in the joint best basis search.
(2) Search down the levels in the tree to find a level where the approximations and details both contain energy.
(3) Use these details for the fault detection.

The core idea in this method is to find a frequency interval which does not contain the lowest frequencies and still contain a relative large part of energy of the fault. It related filter is subsequently used for the fault detection.

4. RESULTS

This method is subsequently used on $\alpha_{\mathrm{f}}[n]$ and $\alpha_{\mathrm{r}}[n]$. The Haar wavelet, see (Mallat 1999), is used for both signals, since it is well suited for detection changes in the signal, and it is short in terms of filter elements. The method is first used to analyze the $\alpha_{\mathrm{f}}[n]$ residual signals. By using the heuristic method, the interesting part of the tree of variance can be seen in Fig. 2. The figure starts with the original variance signal. The remaining figure parts are located by denoting a low-pass filtering with h and high-pass filtering with g, meaning that two low-pass filterings followed by one high-pass, are denoted hhg. The second plot is h, the

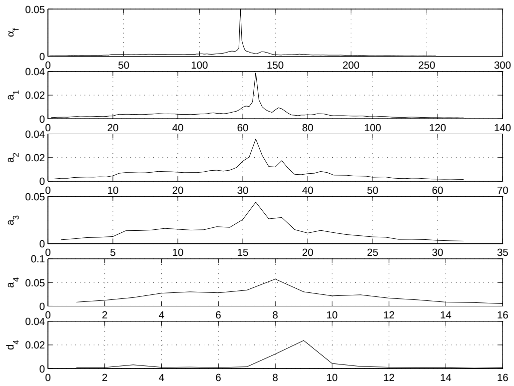

Figure 2. The part of the tree of variance of $\alpha_{\mathrm{f}}[n]$, which is interesting in the used method. The figure starts with the original variance signal. The second plot is h, the third is hh, the fourth is hhh, the fifth is $hhhh$ and the last one is $hhhg$.

third is hh, the fourth is hhh, the fifth is $hhhh$ and the last one is $hhhg$. Notice the large change from hhh to $hhhh$, which results in a significant signal in $hhhg$. The details with low energy have been left out in the plot. This signal is useful for fault detection, since it has relatively large signal parts, and does not contain the near zero frequencies, where disturbances are dominating. This means that a useful filter for fault detection in $\alpha_{\mathrm{f}}[n]$ is found. It is three Haar low pass filters followed by one Haar high-pass filter. The wavelet filters are in the fault detection used as normal FIR filters, where the wavelet filter coefficients are used as the coefficients in a FIR filter. I.e.

$$y[n] = a_1 \cdot x[n] + a_2 \cdot x[n+1] + \ldots + a_N \cdot x[n+N-1], \quad (5)$$

where N is the length of the filter. In contrast to the normal usage of the wavelet packet filters where the output, $y[n]$, depends on both causal and non-causal inputs $x[n]$, and is processed block by block. Instead, a filtered signal is computed at each sample. The wavelet packet analysis is whereby used to analyze the data and based on this design a FIR-filter.

The same method is applied to $\alpha_{\mathrm{r}}[n]$, using the same wavelet, the Haar wavelet. The interesting part of the tree of variance can be seen in Fig. 3. The figure starts with the original signal. The remainder of the figure is in the focus case, however, the analyze stops a level earlier in the radial case. Notice the large change from hh to hhh, which results in a significant signal in hhg. This signal is useful for fault detection, since it has relatively large signal parts, and does not contain the very low frequencies, where disturbances are dominating. This means that a useful filter for fault detection in $\alpha_{\mathrm{r}}[n]$ is found. It is two Haar low-pass filters followed by one Haar high-pass filter. Notice the difference in the structure of the two filters, this is caused by a difference in

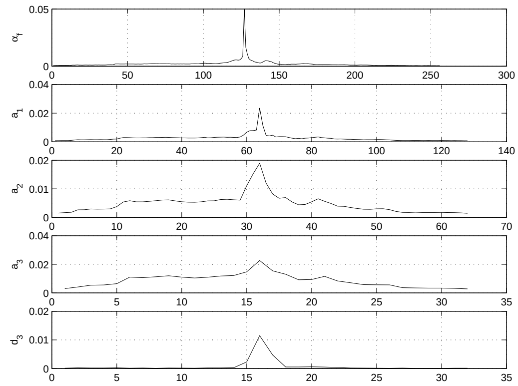

Figure 3. The part of the tree of variance of $\alpha_{\mathrm{r}}[n]$, which is interesting in the used method. The figure starts with the original signal. The second plot is h, the third is hh, the fourth is hhh, and the last one is hhg.

frequency content of the fault in the focus and radial signals.

4.1 Verification and comparison of the method

A zoom on a fault from the test set, is shown in Fig. 4. From this figure it is seen that the filtered signal starts with negative values and subsequently takes positive values. The first part is a response to the beginning of the fault and the second one is response to the last part of the signal. This means that the detection of the beginning of the fault, can be performed by the absolute filtered signal's first crossing of a threshold. The end is detected by the fourth crossing of this threshold, where the absolute filtered signal is lower than the threshold. This approach is illustrated by Fig. 4.

A threshold is subsequently used on these signals to locate the surface faults in time, see Fig. 4, or in other words to detect the faults. The threshold is found as the smallest one which does not result in any false detections. The wavelet based method is compared with a visual identification of the location of the fault, and a standard threshold method, the results can be seen in Table 1. The tables show the detection delays for the standard threshold method and the wavelet packet based method. Detection delay in beginning of a fault means the number of samples the detection of the beginning are delayed compared with the actual beginning of the fault. Detection delay of the end of fault means the number of samples the end is detected earlier than the actual end of the fault.

By comparing the results of the derived wavelet packet based method with a standard threshold method, it can be seen that the wavelet packet filter detection is at least as good as the normal threshold method. It improves the end detection for all the scratches applied in the test examples with up to 3 samples and improves the beginning

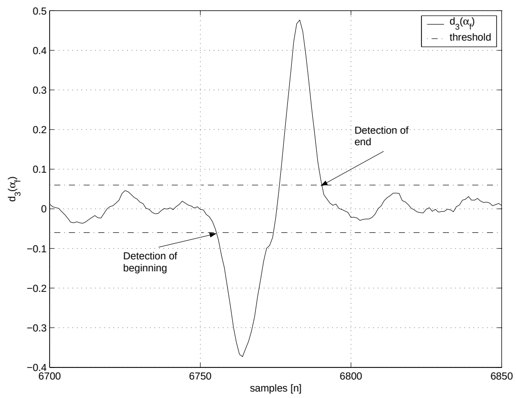

Figure 4. A zoom on a scratch in $e_{\mathrm{f}}[n]$ filtered with three Haar low-pass filters followed by one high-pass filter.

detection in 3 out of 4 test examples. For some faults the wavelet packet method is clearly better, and one should remember the experience that even an improvement of a few samples can be of large importance in the handling of the surface faults. This means that it is of interest to use this joint best basis based wavelet packet filtering method for detection of surface faults on CDs. In addition the use of other wavelets might improve the time localization of the proposed method. This approach for detecting surface faults is expected usable in the newer generations of optical disk drives such as DVDs and Blue-Ray disks.

5. CONCLUSIONS

The topic of this paper has been focused on detection of the scratches (surface faults) on CDs. It is important to have a good detection of the scratch, in accommodating scratches on CDs it is an important task to detect the scratch precisely. In this paper a joint best wavelet basis method based method is used to design a pair of wavelet packet filters for detecting and locating the scratches. These filter based detections are compared with standard thresholding detection methods, and it seems, for the faults in test, the wavelet packet filters detect the scratches better than the normal thresholding method. With up to 3 samples in the tested examples, and one should have in mind that an improvement of the detection of 3 samples is important in this application.

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Fault	α_{f}, α_{r}	Normal (beg.)	Normal (end)	WP (beg.)	WP (end)
#1	α_{f}	13	5	6	4
	α_{r}	7	7	5	4
#2	α_{f}	2	4	1	1
	α_{r}	5	7	2	4
#3	α_{f}	2	3	2	1
	α_{r}	3	5	2	3
#4	α_{f}	21	5	6	3
	α_{r}	22	6	21	3

Table 1. The detection of the four scratch examples, where the wavelet packet based method is compared with normal used standard threshold method. In the table the detection delays of these two methods for the four examples are shown.

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