A REPORT ON

SIGNAL PROCESSING TECHNIQUES FOR STRUCTURAL HEALTH MONITORING (SHM)

FOR PARTIAL FULFILLMENT OF

LABORATORY ORIENTED PROJECT

Submitted by

NAMAN MAHESHWARI 2011A3PS199P

SAHARSH AGARWAL 2011A8PS276P

MENTOR & GUIDE - DR. KOTA SOLOMON RAJU

BITS PILANI, PILANI-333031

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Last but not the least there were so many who shared valuable information which helped in the successful completion of this project.

ABSTRACT

Structural health monitoring (SHM) refers to automated methods for determining adverse changes in the integrity of mechanical systems. Key components of the SHM process include data acquisition and normalization, feature extraction and information condensation, and statistical model development.

i. Damage Detection – It refers simply to the ability to detect whether or not a structure is damaged.
ii. Damage Localization – In this, an effort is made to identify the region of the structure with damage.
iii. Damage Assessment - If the location of the damage can be determined, the next level is to assess the severity of the damage.
iv. Life Prediction - Once the damage assessment has been made, the last level would be to predict the remaining life of the structure.

This report deals with the Matlab Implementation of DWT algorithm. The applications of DWT in SHM are also discussed.

It is a general conclusion that the damage is more detectable for a weaker noise and severer damage. The approach may be implemented both on-line and off-line, and therefore shows great promise for on-line health monitoring, integration with structural control, and post event damage as-sessment.

Wavelet analysis has recently emerged as a promising tool for SHM and damage detection. Cumulative damage of a building with bilinear restoring force subjected to a real earth-quake ground motion was estimated in terms of the accumu-lated ductility ratio, which is related to the number of spikes in the wavelet results.

INTRODUCTION

Structural health monitoring (SHM) refers to automated methods for determining adverse changes in the integrity of mechanical systems. Key components of the SHM process include data acquisition and normalization, feature extraction and information condensation, and statistical model development. Data acquisition includes optimizing the number and placement of sensors on the structure and ensuring that the sensors are robust enough to enable accurate measurements over the life of the structure. Normalization is necessary to account for undesired effects such as changes in environmental conditions and sensor-to-sensor variability followed by the extraction of features to check the condition of the structure. Signal processing issues relating to the key SHM components will be discussed.

Structural health monitoring (SHM) refers to automated methods for determining adverse changes in the integrity of mechanical systems. In the literature, the capability of SHM systems is typically broken down into the following levels of increasing difficulty:

v. Damage Detection – It refers simply to the ability to detect whether or not a structure is damaged.

vi. Damage Localization – In this, an effort is made to identify the region of the structure with damage.

vii. Damage Assessment - If the location of the damage can be determined, the next level is to assess the severity of the damage.

viii. Life Prediction - Once the damage assessment has been made, the last level would be to predict the remaining life of the structure.

The use of SHM systems is being investigated primarily for civil and aerospace structures, largely due to the size, cost, and potential consequences resulting from the failure of such structures.

SHM is essentially an application of statistical pattern recognition. In this approach, a collection of baseline measurements is recorded for various states of the structure including, at a minimum, the undamaged ("healthy") structure. In the "testing" phase, subsequent measurements are compared to the baseline measurements and the decision system predicts the most likely structural state. Factors that can affect the measurements must be accounted for in the training phase for good SHM system performance during testing. Key components in applying statistical pattern recognition to the SHM process include data acquisition and normalization, feature extraction and information, condensation, and statistical model development.

VARIOUS STAGES OF SHM

Data Acquisition

Various parameters must be measured throughout the structure of interest and utilized to determine the condition, or state, of the structure. Therefore, it is necessary to define the type, number, and placement of sensors on the structure. All of these factors are problem dependent. To describe the steps, example is given for the development of a SHM system to detect fastener failures in a thermal protection system (TPS) panel as shown in the figure. The structural damage states of interest are if any of the 15 bolts fastening the carbon-carbon panel to the brackets are loose or missing.

Fig. 1 Front and back views of thermal protection system assembly used for fastener failure detection and localization studies

Normalization

Normalization is applied to account for changes in structural response due to environmental conditions or structural loads which are not associated with any structural damage. For example, the elastic modulus of a structure, which is often temperature-dependent, may have a significant affect on the structural dynamics. Normalization is necessary to insure that changes in the structural dynamics due to temperature are not interpreted as damage. The TPS assembly utilizes piezoelectric transducers which are bonded to the surface of the backing structure. The amplitude levels recorded by the piezoelectric transducers can vary depending on the bond quality, the temperature of the piezoelectric transducer, the gain of individual transducers, or other factors. Since these changes do not relate to the damage state of the structure, normalization is required to account for such changes.

Feature Extraction

Feature extraction is the process of computing metrics from sensor signals that have the potential to discriminate among the structural states to be identified. Desirable features are ones that are responsive to the structural damage states, yet insensitive to other factors. In practical applications, however, it is often the case that features that are sensitive to damage are also sensitive to environmental or operational factors. Fastener failures in the TPS assembly are simulated by individually loosening one of the fifteen bolts connecting the carbon-carbon panel to the standoff brackets. When a bolt is loosened, the resonant frequencies and mode shapes of the assembly change depending on the location of the loose bolt. The frequency dependencies are measured by computing 100-point power spectral densities at the three sensing piezoelectric transducers. A "feature vector" is formed by concatenating all measurements into a single 300-element vector.

Dimensionality Reduction

Although a large number of features can be created during the feature extraction step, a subset is usually selected prior to the statistical pattern recognition step. In general, reducing the number of features used to "train" a classifier increases the likelihood that the performance during the training phase will be representative of the performance during testing. Feature selection is the process of finding a subset of the original features. Feature selection methods can be categorized into filter methods and wrapper methods. In a filter method, relevant features are determined based solely on attributes computed from the data. In wrapper approaches, relevant features are determined based on how well a subset of features performs when used in a classifier. In addition to feature selection, projection of the original feature space into a lower dimensional subspace is another form of dimensionality reduction. Principle components analysis (PCA) is a projection method commonly used for dimensionality reduction.

Statistical Pattern Recognition

For SHM system development, the statistical pattern recognition approach has been applied with one discriminant function used to represent each structural damage state of interest. The lowest average probability of classification error is provided when the discriminant functions are the class-conditional probability density functions (pdf's). Therefore the statistical pattern recognition design process is essentially one of density estimation. Non-parametric and parametric methods can be used for density estimation. A non-parametric density estimation method does not require any assumptions about the distribution of the data. Types of non-parametric density estimates include Parzen Windows and k-nearest neighbors. Parametric density estimation methods assume a functional form of the underlying class-conditional densities. A Gaussian distribution is commonly assumed since it requires defining only two parameters, the mean and covariance matrix, which are easily computed.

Elastic Wave Techniques – Lamb Waves

For many aerospace structures, an essential challenge is to monitor a large area for localized damage such as cracking or corrosion. Higher frequencies are better suited for detecting localized damage such as cracking or corrosion. Lamb waves are guided elastic waves that occur in a free plate and hence, are of high frequencies. Lamb waves can exhibit symmetric and anti-symmetric waveforms, based on whether the out-of-plane displacements on either side of the plate are in or out of phase. Lamb waves also are dispersive and the wave speed, or phase velocity, is a function of frequency. Due to dispersion, Lamb waves become distorted as they propagate.

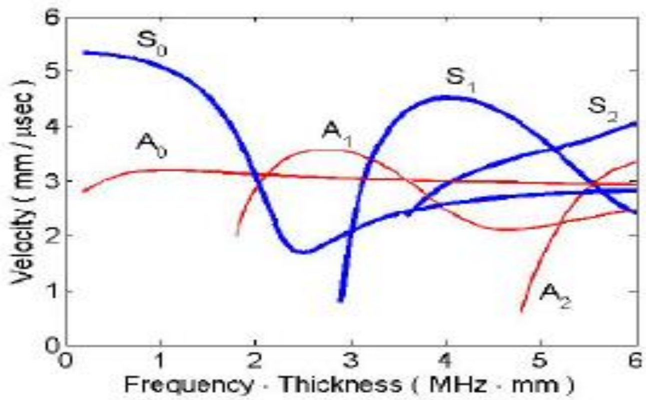


Fig. 3 Lamb wave group velocity dispersion curves for aluminum.

To limit the number of coexisting waveforms, the excitation frequency is typically kept relatively low such that only the So and Ao waveforms will exist. These waveforms, So and AO, are referred to as the fundamental modes and are typically used for Lamb wave damage detection. As a general rule, elastic waves can be used to detect damage on the order of the wavelength. The Ao Lamb mode has a much lower wave speed than the So mode, and therefore has a smaller wavelength, making it more sensitive to smaller levels of damage. For SHM applications, Lamb waves can be generated by bonding piezoelectric transducers to the surface of a plate and sending an appropriate input signal. In the literature, a common excitation signal is a Hanning-windowed sinusoidal burst with an integer and a half number of cycles. These Lamb wave packets propagate through the structure at the speeds determined by the group velocity dispersion curves and interact with damage. For example, the wave packets may reflect off crack boundaries or attenuate when passing through thinner, corroded regions.

Structural Health Monitoring of Bridges Using Wireless Sensor Networks

Aging and degradation of transportation infrastructure, especially for critical structures such as bridges, pose significant safety concerns, especially in light of increased use of these structures. The US Federal Highway Administration has classified over 25% of the bridges in the United States as either structurally deficient or functionally obsolete, underscoring the importance of structural health monitoring (SHM) to ensure public safety. An overview of emerging wireless sensor networks (WSN) for autonomous SHM systems is given along with their their application, the power use and sources needed to support autonomy, and the type of communication that allows remote monitoring. Several wired SHM systems have been developed, but they suffer from high cost, inadequate design, difficult installation, or some combination of these shortcomings. Their high power consumption constrains their deployment to locations with access to the power grid, as alternative or portable power sources are rarely adequate. A more important constraint associated with the use of wired SHM systems is the wiring required to supply power and interconnect components of the system. This difficulty in retrofitting hampers their utility and hence, wireless systems are preferred. Several existing SHM systems use wireless communication to allow devices to coordinate and collaborate to more effectively measure a structure, whether the goal is improved spatial resolution, network resilience, or advanced *in-situ* analysis.

The majority of these systems are based on general-purpose sensing platforms, or motes, such as the Tmote Sky by Moteiv, and Mica and MicaZ by Crossbow. The systems are typically capable of communicating wirelessly over a range of 100 m, using a 2.4 GHz 802.15.4 transceiver. Field testing of a number of these systems provides strong evidence of the effectiveness of wireless SHM, with results reported within 0.1% of those measured using wired sensors for vibration analysis. However, most of these systems suffer from high power consumption, yet they are generally equipped with a limited power supply. Although most wireless SHM systems use ZigBee (or another 802.15.4-based communication protocol), which is ideal for low-power, low-data rate communications, there are a few projects that employ Bluetooth or Wi-Fi to communicate within the network. Both of these technologies work in the same frequency range and provide better data throughput than ZigBee but with much higher power consumption.

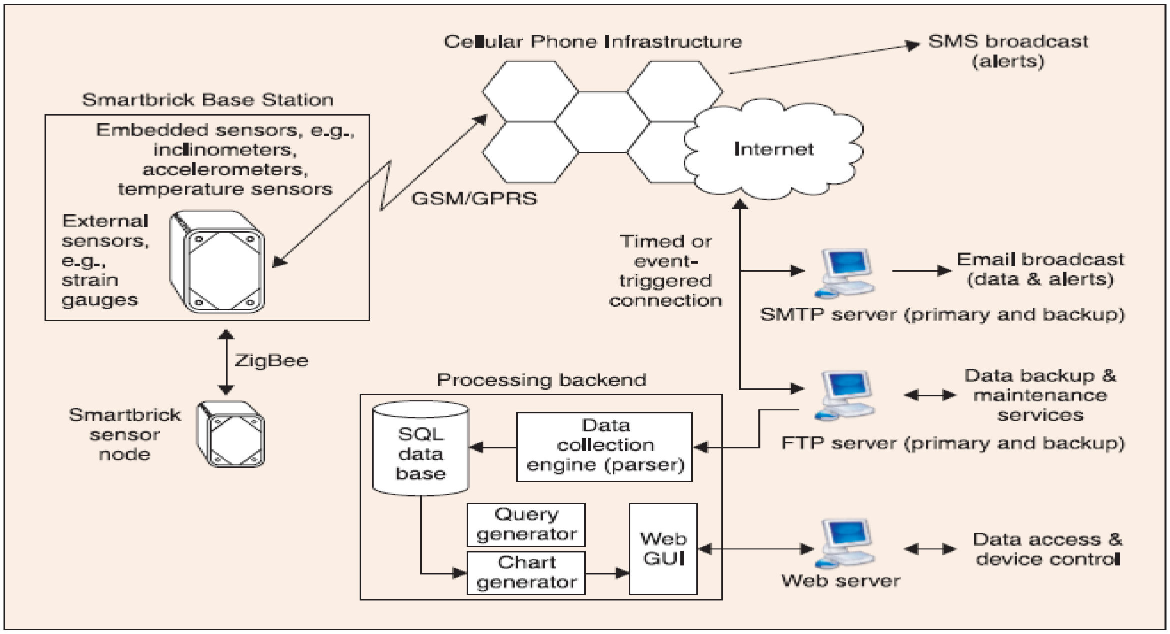


Fig. 1. Block Diagram of the SmartBrick Platform [6]. (© 2009 IEEE, *Proc. of 12th IEEE Int'l. Conf. on Intelligent Transportation Systems*, used with permission.)

Time-triggered data acquisition takes place at regular intervals which can be specified remotely through the web interface. Data from quasi-static sensors, e.g., temperature sensors and strain gauges, are collected in this fashion. The parameters monitored by these sensors are not subject to rapid or sudden changes, and periodic collection of their values suffices. The acquired data are written to memory and scanned for abnormalities in trend or level. The detection of any abnormality generates an "alert" condition where a message is broadcast through the redundant channels mentioned above, and the data are uploaded to the server. Sudden changes trigger event-based data collection from the sensors that could corroborate the existence of a threat. For example, the data collected by seismic detectors because of an earthquake can change very rapidly, and such a change can indicate a significant safety hazard. Fast Fourier transform processing and thresholding are carried out to compress the data before writing it to memory or reporting it to remote recipients.

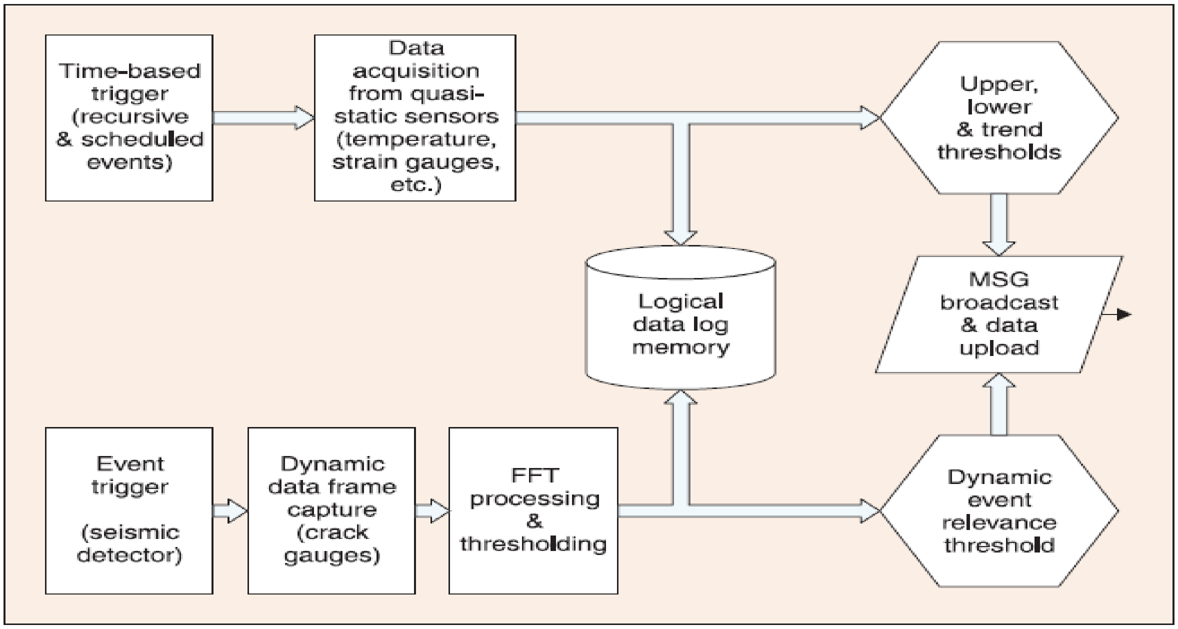


Fig. 3. Data flow in the SmartBrick wireless sensor network [2]. (© 2009 IEEE, *Proc. of 12th IEEE Int'l. Conf. on Intelligent Transportation Systems,* used with permission.)

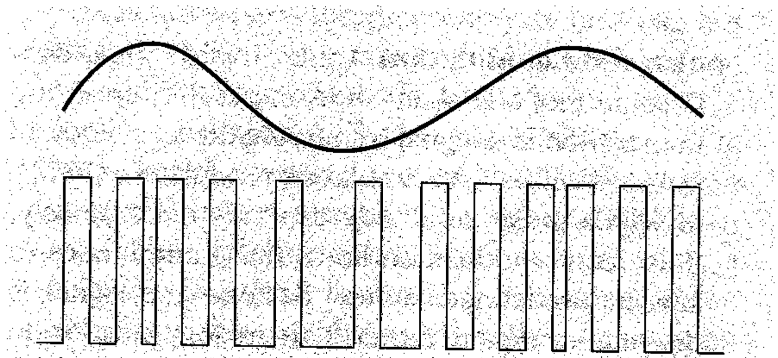
Automatic guided wave PPM communication system for potential SHM of flooding members in sub-sea oilrigs

An acceptable alternative to close visual inspection (CVI) is a non-destructive testing (NDT) technique called flood member detection (FMD). It employs ultrasound or x-rays to detect the presence of seawater in the tubular structures. The system employs two smart sensors and modulators, which transmit 40 kHz guided wave pulses, and a digital signal processing demodulator, which performs automatic detection of guided wave energy packets. Results confirm that, although there was significant dispersion of the transmitted pulses, the system successfully distinguished automatically guided wave encoded information that could potentially be used in sub-sea oilrigs.

This work presents the initial results obtained from an automatic pulse position modulation (PPM) system that could be used for SHM of tubular members in fixed offshore oilrigs, innovatively using the tubular structure as a communication channel. System employs a single PZT transducer, which is permanently attached to the inner wall of the lower end of a given sub-sea crossbeam, and is powered by a (normally inert) seawater battery. The system transmits 40 kHz ultrasonic guided waves pulses through hollow steel tubes. The system employs two smart transmitter modulators composed of a PZT element, electronics and batteries, and demodulator instrumentation that is made of a PZT ultrasound transducer, a real-time digital signal processing

(DSP) board and a PPM module based on a microcontroller, which performs automatic PPM detection of guided wave energy packets.

Upon activation, the sensor transmits ultrasonic chirp or tone encoded pulses, in the range of 21–42 kHz, to a monitoring receiver system at deck level for decoding and identifying flooded members. Narrow band signals are often used as excitation for NDT purposes in order to give good signal strength and to avoid dispersion over long propagation distances. Tone pulses of between 5 and 10 cycles modulated by a Hanning or a Gaussian window are frequently employed. PPM is a form of signal modulation in which the message information is modulated through variable time delays between pulses in a sequence of signal pulses. The electronics required to demodulate the PPM signals are simple



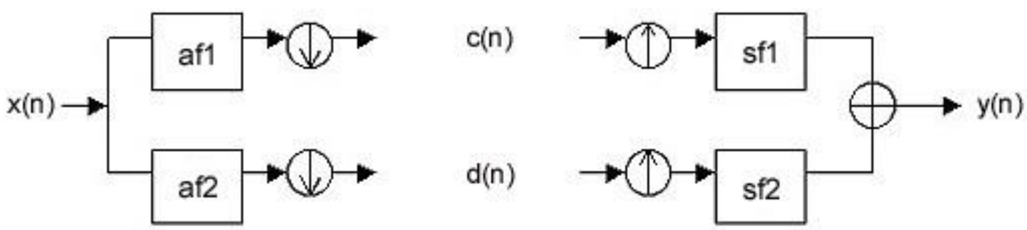
Pulse position modulation.

A series of experiments were conducted, in dry conditions, in the laboratory and outside the laboratory using tubular steel structures as guided wave communication channels. Initially the automatic guided waves system was tested in the laboratory to establish that the transmitter modules, receiver and digital filtering systems were operating correctly. In this application, permanently attached smart sensors that derive benefit from guided ultrasonic waves offer a promising alternative future for FMD systems for remote real-time SHM of sub-sea steel structures in oilrig offshore platforms. In this work, however, the emphasis is in the automatic detection of guided wave pulses using PPM for encoding information of different transmitters. Results show that by exploiting the waveguide effect of steel pipes, which act as communication channels, successful transmission and reception of PPM encoded information has been achieved.

DWT IMPLEMENTATION ALGORITHM

1. 2-Channel Perfect Reconstruction Filter Bank

The analysis filter bank decomposes the input signal x(n) into two subband signals, c(n) and d(n). The signal c(n) represents the low frequency (or coarse) part of x(n), while the signal d(n) represents the high frequency (or detail) part of x(n). The analysis filter bank first filters x(n) using a lowpass and a highpass filter. We denote the lowpass filter by af1 (analysis filter 1) and the highpass filter by af2 (analysis filter 2). As shown in the figure, the output of each filter is then down-sampled by 2 to obtain the two subband signals, c(n) and d(n).



The Matlab program below, afb.m, implements the analysis filter bank. The program uses the Matlab function upfirdn (in the Signal Processing Toolbox) to implement the filtering and downsampling.

Matlab function afb.m

```
function [lo, hi] = afb(x, af)

% [lo, hi] = afb(x, af)
%
% Analysis filter bank
% x -- N-point vector (N even); the resolution should be 2x filter length
%
% af  -- analysis filters
% af(:, 1): lowpass filter (even length)
% af(:, 2): highpass filter (even length)
%
% lo: Low frequency
% hi: High frequency
%

N = length(x);
L = length(af)/2;
x = cshift(x,-L);

% lowpass filter
lo = upfirdn(x, af(:,1), 1, 2);
lo(1:L) = lo(N/2+[1:L]) + lo(1:L);
lo = lo(1:N/2);
```

```
% highpass filter
hi = upfirdn(x, af(:,2), 1, 2);
hi(1:L) = hi(N/2+[1:L]) + hi(1:L);
hi = hi(1:N/2);
```

The synthesis filter bank combines the two subband signals c(n) and d(n) to obtain a single signal y(n). The synthesis filter bank first up-samples each of the two subband signals. The signals are then filtered using a lowpass and a highpass filter. We denote the lowpass filter by sf1 (synthesis filter 1) and the highpass filter by sf2 (synthesis filter 2). The signals are then added together to obtain the signal y(n). If the four filters are designed so as to guarantee that the output signal y(n) equals the input signal x(n), then the filters are said to satisfy the perfect reconstruction condition. The Matlab program below, sfb.m, implements the synthesis filter bank.

Matlab function sfb.m

```
function y = sfb(lo, hi, sf)

% y = sfb(lo, hi, sf)
%
% Synthesis filter bank
%

% lo - low frqeuency signal
% hi - high frequency signal
% sf - synthesis filters
% sf(:, 1) - lowpass filter (even length)
% sf(:, 2) - highpass filter (even length)
%
% y - output

N = 2*length(lo);
L = length(sf);
lo = upfirdn(lo, sf(:,1), 2, 1);
hi = upfirdn(hi, sf(:,2), 2, 1);
y = lo + hi;
y(1:L-2) = y(1:L-2) + y(N+[1:L-2]);
y = y(1:N);
y = cshift(y, 1-L/2);
```

The following code fragment shows an example of how to use the Matlab functions, afb.m and sfb.m. This example verifies the perfect reconstruction property. First, we create a random input signal x of length 64. Then the analysis and synthesis filters are obtained with the Matlab function farras.m.

Matlab Function Farras.m

```
function [af, sf] = farras
af = [
                  0  -0.01122679215254
                  0   0.01122679215254
  -0.08838834764832   0.08838834764832
   0.08838834764832   0.08838834764832
   0.69587998903400  -0.69587998903400
   0.69587998903400   0.69587998903400
   0.08838834764832  -0.08838834764832
  -0.08838834764832  -0.08838834764832
   0.01122679215254                  0
   0.01122679215254                  0
];

sf = af(end:-1:1, :);
```

The two subband signals (here called lo and hi) are computed with the function afb.m. The output signal y is then computed using the Matlab function sfb.m. The maximum value of the error x - y is computed, and it is equal to zero (within computer precision). This verifies the perfect reconstruction property.

A couple of remarks about the programs afb.m and sfb.m. Suppose the input signal x(n) is of length N. For convenience, we will like the subband signals c(n) and d(n) to each be of length N/2. However, these subband signals will exceed this length by L/2, where L is the length of the analysis filters.

To avoid this excessive length, the last L/2 samples of each subband signal is added to the first L/2 samples. This procedure (periodic extension) can create undesirable artifacts at the beginning and end of the subband signals, however, it is the most convenient solution. When the analysis and synthesis filters are exactly symmetric, a different procedure (symmetric extension) can be used, that avoids the artifacts associated with periodic extension.

A second detail also arises in the implementation of the perfect reconstruction filter bank. If all four filters are causal, then the output signal y(n) will be a translated (or circularly shifted) version of x(n). To avoid this, we perform a circular shift in both the analysis and synthesis filter banks. The circular shift is implemented with the Matlab function cshift.m.

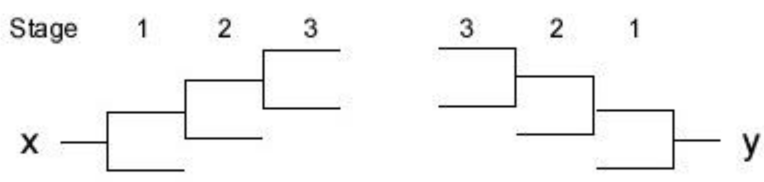
Matlab Function cshift.m

```
function y = cshift(x, m)

% Circular Shift
%
% USAGE:
%    y = cshift(x, m)
% INPUT:
```

```
%    x - N-point vector
%    m - amount of shift
% OUTPUT:
%    y - vector x will be shifed by m samples to the left
%
% WAVELET SOFTWARE AT POLYTECHNIC UNIVERSITY, BROOKLYN, NY
% http://taco.poly.edu/WaveletSoftware/

N = length(x);
n = 0:N-1;
n = mod(n-m, N);
y = x(n+1);
```

2. Discrete Wavelet Transform (Iterated Filter Banks)

The discrete wavelet transform (DWT) gives a multiscale representation of a signal x(n). The DWT is implemented by iterating the 2-channel analysis filter bank described above. Specifically, the DWT of a signal is obtained by recursively applying the lowpass/highpass frequency decomposition to the lowpass output as illustrated in the diagram. The diagram illustrates a 3-scale DWT. The DWT of the signal x is the collection of subband signals. The inverse DWT is obtained by iteratively applying the synthesis filter bank.



The Matlab function dwt.m below computes the J-scale discrete wavelet transform w of the signal x. We use the cell array data structure of Matlab to store the subband signals. For j = 1..J, w{j} is the high frequency subband signal produced at stage j. w{J+1} is the low frequency subband signal produced at stage J.

The inverse DWT is computed with the Matlab function idwt.m. The perfect reconstruction of the DWT is verified in the following example. First we create a random input signal x of length 64. Then the analysis and synthesis filters are obtained with the Matlab function farras.m. The 3-scale DWT is computed with the function dwt.m. The inverse DWT is then computed to get the signal y. As verified below, y = x within computer precision.

EXAMPLE (VERIFY PERFECT RECONSTRUNCTION OF DWT)

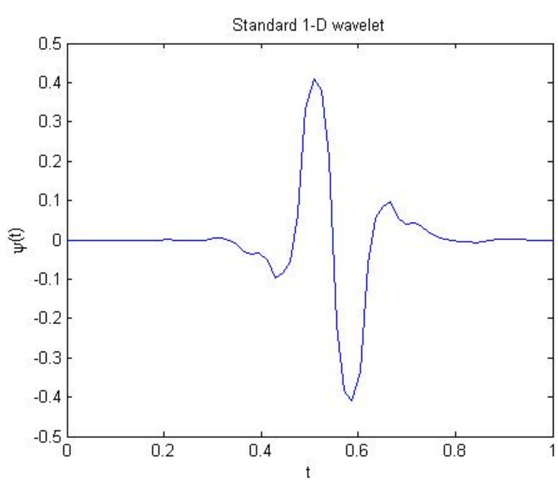
```
>> [af, sf] = farras;      % analysis and synthesis filter
>> x = rand(1,64);         % create generic signal
>> w = dwt(x,3,af);        % analysis filter banks (3 stages)
```

```
>> y = idwt(w,3,sf);       % synthesis filter banks (3 stages)
>> err = x-y;              % compute error signal
>> max(abs(err))           % verify that error is zero

ans =

  4.2633e-014
```

The wavelet associated with a set of synthesis filters can be computed using the following Matlab code fragment. In this example, we set all of the wavelet coefficients to zero, for the exception of one wavelet coefficient which is set to one. We then take the inverse wavelet transform.

COMPUTING THE WAVELET

```
>> [af, sf] = farras;     % analysis and synthesis filters
>> x=zeros(1,64);         % create zero signal
>> w = dwt(x,3,af);       % analysis filter bank (3 stages)
>> w{3}(5)=1;             % set single coefficient to 1
>> y = idwt(w,3,sf);      % synthesis filter bank (3 stages)
>> plot(0:63,y);          % Plot the wavelet
>> axis([0 63 -0.5 0.5]);
>> title('Standard 1-D wavelet')
>> xlabel('t');
>> ylabel('\psi(t)');
```



Different Techniques for SHM

Various different techniques for the stages of SHM are listed below along with the references –

DAMAGE DETECTION

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- Non-parametric evaluation with statistical pattern recognition for damage detection
  Mustafa Gül, (2009) "Investigation of damage detection methodologies for Structural health monitoring "

- Wireless Sensor System for Structural Health Monitoring, Bridge Safety, Damage Detection
  Technology #4756, http://inventions.umich.edu/technologies/4756_wireless-sensor-system-for-structural-health-monitoring-bridge-safety-damage-detection

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Caffrey, Ramesh Govindan and Erik Johnson, Computer Science and Civil Engineering Depts., Univ. of Southern California "Structural Damage Detection and Localization Using NETSHM"

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- Using elastic waves propagation method

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  Ju-Won Kima, Changgil Leea & Seunghee Parka, Research in Nondestructive Evaluation Volume 23, Issue 4, 2012, “Damage Localization for CFRP-Debonding Defects Using Piezoelectric SHM Techniques”

- Using EMI spectrums and IDW interpolation

  “Damage localization map using EMI spectrums and IDW interpolation: Experimental validation on thin composites structures”, Structural Health Monitoring 1475921713493343, first published on June 19, 2013

DAMAGE ASSESSMENT

- Using Measured FRFs from Multiple Sensors

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