M10.10 Signal Abstractions in the Machine Analysis of Radar Signals for Ice Profiling

S. Lee[1], E. Milios[2], R. Greiner[2], J. Rossiter[3]

[1] Dept. of Elec. Eng., University of Toronto, Ont., Canada M5S 1A4
[2] Dept. of Computer Science, University of Toronto, Ont., Canada M5S 1A4
[3] Canpolar Inc. Ltd.

Abstract

This paper describes the design and implementation of an automated system for interpreting impulse radar signals for ice thickness profiling. We have adopted an integrated approach which includes numeric computation in the form of deconvolution filtering with rule-based classification of signal features at multiple levels. Noise reduction and deconvolution techniques are used to enhance the radar signals for better resolution of overlapping events. Motivated by human perceptual (visual) knowledge, a hierarchy of data structures is constructed as representations of signal characteristics at various levels of abstraction. Classification rules, based on the protocols collected from an expert, physical constraints on the helicopter motion and the nature of the radar signals are used to produce the current signal interpretation. A prototype system has been implemented on the Symbolics Lisp Machine and tested on real data.

I. Introduction

Making measurements of the thickness of river or sea ice over large distances is important in polar regions for the study of ice dynamics, the tactical planning of transportation routes and the location of under-ice oil entrapment for Arctic petroleum exploration. Because of the enormous size of the ice cover over water, traditional surface measurement method has been gradually given way to impulse radar sounding from the air using either helicopters or small-fixed wing aircraft. Ice thickness can be calculated from radar impulse traveling time between top and bottom reflections, given the speed of radar signal through the ice. In practice, each radar return signal is put side by side to form a *signal image* which is then analyzed for an interpretation of the ice thickness distribution, types and other structural information. The performance objective is to correctly recognize scenes that can be reliably determined from visual interpretation of the data by the human expert.

Among numerous ways of remotely determining the properties of floating ice, radar sounding appears to have better potential to give a continuous profile of ice thickness along a given track for relatively non-saline ice types. *Impulse radar* [10] differs from more conventional types of subsurface radar in that instead of transmitting many cycles of a particular frequency, a broad-band monocycle pulse is transmitted. The advantages of impulse radar are that relatively low frequencies can be used, giving the ability of penetrating "lossy" materials, while retaining adequate time resolution for accurate depth estimates. The main disadvantage is that it is not possible to focus the antenna radiation pattern, which is similar to that of a half-wave dipole. Therefore it is necessary to make measurements on or near the surface in order to achieve reasonable spatial resolution and to receive a strong enough return signal.

The physical principle upon which the method is based is the reflection that occurs when an electromagnetic wave is incident upon an interface where a change in electrical properties occurs. In the impulse radar system under discussion, an extremely short electromagnetic pulse is generated by the radar device mounted under a low-flying helicopter and is radiated downwards towards the ice. Primary reflections or echoes from the top and bottom of the ice are received. The time separation between the top and bottom echoes represents the travel time from the top ice surface to the bottom interface and back. Once the speed of propagation within the ice is known, either from a knowledge of the electrical properties (speed $= \frac{c}{\sqrt{\epsilon}}$, ϵ is the ice dielectric constant) or from direct mechanical calibration by measurement of ice thickness, then the travel time can be converted directly to ice thickness. Subsurface is assumed to be consisted of homogeneous, isotropic and parallel layers and secondary reflections are negligible.

A signal image, $I[i,j]$ is formed by putting consecutive traces side by side ($I[i,j] \triangleq y_i[j]$). In the signal image, the x-axis represents horizontal displacement, the y-axis represents vertical depth from the impulse radar while intensity values are proportional to the strength of return radar echoes. Such an image can be interpreted as depicting the ice layer's substructure along a vertical cross-sectional plane. Each trace $y_i[n]$ (i is the trace index and n represents depth) will consist of an ice surface reflection followed by an ice-bottom reflection for the case of ice, or just an air-water reflection from open water if there is no ice.

II. System Overview

We decompose the interpretation task as follows: (A) Image processing to enhance the radar image for visual clarity. (B) Construction of a hierarchy of signal abstractions corresponding to the signal structures the human expert visually concentrates on. (C) Interpretation using classification rules. The overall architecture of the impulse radar signal interpretation system based on the above decomposition is shown in Figure 1.

III. Preprocessing and Deconvolution

Several radar traces are *stacked* (averaged) to reduce jitter noise and the amount of subsequent processing is also alleviated. A Gaussian kernel N(0,σ), defined as $Gauss_{N(0,\sigma)}(i,j) = \frac{1}{2\pi\sigma^2}\, exp(-\frac{i^2+j^2}{2\sigma^2})$, is convolved with the signal image to smooth out sharp changes. It is a 2-D low pass filtering operation.

The probing waveform of our impulse radar system is not a true impulse, but a wavelet (triplet) of very short duration. The echoes from various (lossy) interfaces will appear as time-shifted and distorted versions of this probing wavelet. Visual identification of these interface boundaries is particularly difficult when distances between interfaces are small, causing wavelets from different interfaces to merge together. The idea of *deconvolution* is to remove the effect of the probing wavelet by collapsing each "replica" of the probing wavelet to an impulse at the appropriate position and with the appropriate amplitude and phase. The resulting simplified waveform will then be a sequence of impulses where various reflecting interfaces can be identified more easily.

In ice thickness profiling applications, the signal at the receiver at a particular position can be represented as

$$y(n) \quad = \quad x(n) \star h(n) + u(n) \qquad (1)$$

where $u(n)$ is the measurement noise, $x(n)$ is a sequence associated with the basic signature wavelet, and $h(n)$ is the reflection coefficient sequence corresponding to various "stratigraphic" events.

To implement deconvolution, an average wavelet selected from a region of strong reflections from open-water was taken as the signature wavelet. Based on preliminary analyses and experimental testing of several simple deconvolution filters, Riad compensator [9], defined in equation 2, is best suited to our problem with its flexibility and low computational cost.

$$H(\Omega) \quad = \quad \frac{Y(\Omega)}{X(\Omega)} \cdot \frac{1}{1 + \frac{\alpha}{X(\Omega)^2}} \qquad (2)$$

The filter parameter α is usually optimized using heuristic criteria.

IV. Signal Abstraction

Motivated by human perceptual (visual) knowledge, a hierarchy of data structures is constructed as representations of signal characteristics at various levels of abstraction [1, 7]. Instead of doing the classification by a one-step (direct) discriminant function-like mapping, intermediate symbols are constructed, which are then used as attributes to a higher-level classification process. Symbols at each level are produced by a classification process using the symbols from the previous level as attributes. Each such computational process is much more tractable. We define five levels of abstractions (see Figure 2), based on protocols collected from an expert.

The **Base level** or **Level 0** abstraction is simply the deconvolved image itself which is an array of intensity values. We will regard the image as a collection of POINTs. **Level 1** abstraction is derived from the deconvolution theory which implies that each reflection interface manifests itself in each trace (intensity as a function of y-coordinate) of the deconvolved image as an impulse (or a "sharp" pulse in reality). Peaks of a radar trace correspond to local maxima, therefore they are located at zero crossings of the first difference of the trace. We define a PEAK to denote such a pulse and its associated features.

At each trace, PEAKs that are potential reflection interfaces must be chosen. The essential attributes that characterize a PEAK are: **Strength** - the normalized intensity of the PEAK; and **Symmetry** - the symmetry of the PEAK shape. Histogram statistics of the Strength and Symmetry attributes of PEAKs selected from a region of open water have been used to guide the separation of those candidate PEAKs from noise PEAKs. Open water region statistics were used because the deconvolution signature wavelet was derived from such region and such statistics are reliable and easy to interpret. Guided by these histograms, strong and symmetric PEAKs are selected as candidate PEAKs for interfaces.

The **Level 2** abstraction is aimed to create more global structures based on contextual information. A sequence of neighboring PEAKs with similar characteristics are linked together. Sequences of PEAKs are referred to as EDGELs. Similarity requirements for PEAK linking are simple but very conservative. Only PEAKs in the immediate neighborhood are considered. EDGELs are incrementally built from PEAKs. A PEAK is joined to an EDGEL if the following two conditions are satisfied: (1) small pixel distance between 2 candidate PEAKs; and (2) similar PEAK intensity values. The resulting EDGELs are the "*islands of reliability*".

These basic edge elements, serving as seeds for region growing, are then extended to fill small gaps to form LINEs which are at **Level 3** abstraction. Each LINE is a list of edgels and artificial joints (which connect 2 adjacent edgels). The local geometric constraints for the formation of LINEs from EDGELs [6] based on human visual grouping criteria include: similar EDGEL average intensity, close physical proximity, tolerance for overlap, similar orientations, and smooth connection.

Finally, the highest level or **Level 4** abstraction is a LAYER which is essentially an interval together with its constituent lines. The top reflecting LINE from the top of the ice is strong and consistent, so that the problem is to identify the bottom boundary LINEs for various ice floes. Picking the longest and strongest LINE below the top LINE as the bottom-boundary LINE is the heuristic used to partition LINEs into LAYERs. These high level symbolic structures, LAYERs, constitute the data base which our rule-based deduction system will make inference on.

V. Rule-based Classification

Complex symbolic structures built up from the lower levels are fed into a rule-based interpreter which is a form of *production rule system* [2]. Domain knowledge for ice characterization and classification is derived from the domain expert and is encoded in typical IF-THEN rules to run in the forward chaining mode. Examples of these rules are shown below, with $x denoting a variable.

```
If      $x is an interval
        and
        It cannot be proved that $x does not have a bottom boundary
then    $x is ice


If      $x is ice
        and
        $x has hyperbolae in its bottom
then    there are sharp-pointed features in the bottom of $x
```

VI. Implementation and Results

The complete system was implemented in Zeta Lisp and Common Lisp, running on Symbolics Lisp 3640 Machine. The low level processing involved the use of two software packages: an object-oriented (1-D) signal processing environment - KBSP [3] and a two-dimensional image processing package - ImageCalc [8]. Signal Abstraction employed the Flavors mechanism of Zeta Lisp and rule-based classification used MRS [4].

The system was tested with several data sets from two different field trips. Detailed interpretation results can be found in [5]. A glossary for ice interpretation is shown in Figure 3. Experiments with these data sets have yielded encouraging results about the validity of the approach.

VII. Concluding Remarks

Based on an approximate signal model, human perceptual (visual) knowledge and heuristics, signal abstractions appropriate for the two dimensional signals obtained as reflections from layered propagation media have been developed as a means to integrate pure signal processing algorithms with rule-based signal classification. Our structured framework provides a strong basis for improving the performance of the system. Further research includes automation of threshold setting by establishing feedback between high and low level processes, a more intelligent user interface and incorporating uncertainty handling to deal with noisy data and incomplete knowledge.

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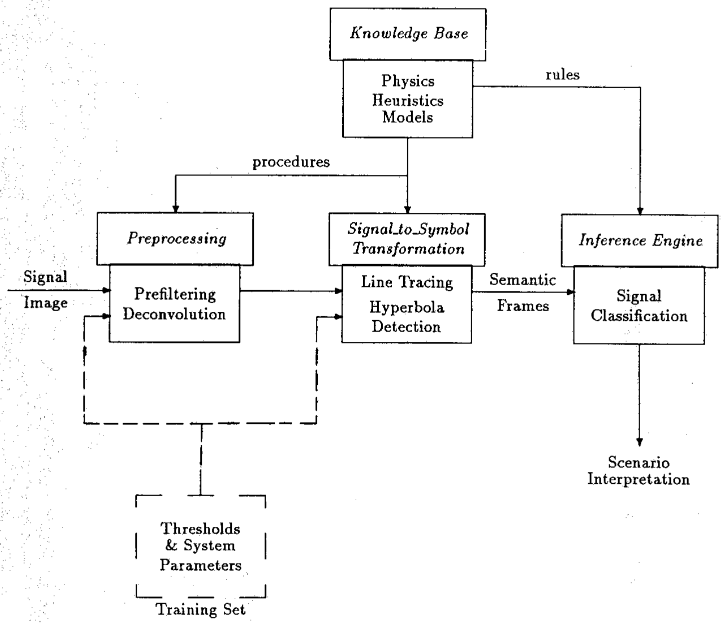

Figure 1: Architecture of the overall system.

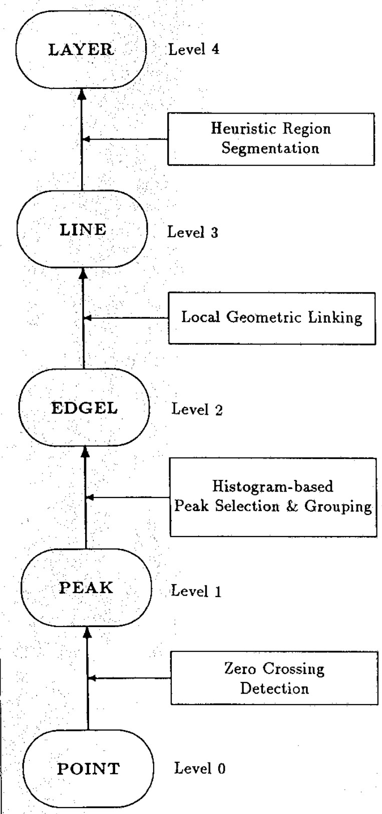

Figure 2: Signal Abstraction Hierarchy & Inter-level Transformations.

Figure 3: A glossary for Ice Interpretation.

Term	Meaning	Sketch
Floe	Large ice piece	
Rubble	Small ice piece	
Thick/Thin/Very-thin	Ice thickness classification	thickness
Damp/Lossy	Undetectable ice bottom at melting/sub-zero temperatures	
Open water	Strong and clear reflection attributed to water region	
Smooth/Rough bottom	Bottom roughness classification	
Sharp features at bottom	Hyperbola(e) detected at ice bottom	