AD-A273 625

254400-1-P

Interim Progress Report

OPTICAL WAVELET TRANSFORM PROCESSOR: Interim Report

Nikola Subotic OCTOBER 1993



Contract No. N00014-93-C-0108

Submitted to: Office of Naval Research 800 North Quincy Street Arlington, VA 22217-5000

3.07 93-29849



P.O. Box 134001 Ann Arbor, MI 48113-4001



93 12 7

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE

	REPORT DOCUM	ENTATION PA	GE		OMB No. 0704-0188
1a REPORT SECURITY CLASSIFICATION Unclassified	1b RESTRICTIVE MARKINGS				
2a SECURITY CLASSIFICATION AUTHORITY		3. DISTRIBUTION/AVAILABILITY OF REPORT			
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE		Unlimited			
4. PERFORMING ORGANIZATION REPORT NUMBE	RS(S)	5. MONITORING C	RGANIZATION REI	PORT NUMBE	R(S)
254400-1-P					
6a. NAME OF PERFORMING ORGANIZATION	6b OFFICE SYMBOL (if applicable)	L 7a. NAME OF MONITORING ORGANIZATION			
ERIM		Office of Naval Research			
6c. ADDRESS (City, State, and ZIP Code) P.O. Box 134001 Ann Arbor, MI 48113-4001		7b. ADDRESS (City, State, and ZIP Code) Ballston Tower One 800 North Quincy Street Arlington, VA 22217-5660			
8a. NAME OF FUNDING /SPONSORING ORGANIZATION	8b. OFFICE SYMBOL (if applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER			
8c. ADDRESS (City, State, and ZIP Code)		10 SOURCE OF F	UNDING NUMBERS		
Ballston Tower One 800 North Quincy Stree		PROGRAM ELEMENT NO.	PROJECT TASK NO. NO.		WORK UNIT ACCESSION NO.
Arlington, VA 22217-5660					
Nikola S. Subotic, Carl C 13a. TYPE OF REPORT 13b. TIME C Interim FROM_6/1 16. SUPPLEMENTARY NOTATION	Aleksoff OVERED <u>10_9/20/</u> 93	4. DATE OF REPORT 93 Nov 22	(Year, Month, Day 2) 15	PAGE COUNT 33
17. COSATI CODES FIELD GROUP SUB-GROUP	18. SUBJECT TERMS (Wavelet Tran Optical Proc Time Integra	Continue on reven sform essor ting Archit	rse if necessary ecture	and identil	ly by block numb e r)
In this report we outline transform of two dimensio	e a time-integrating onal spatial or sp	hybrid-optical ectral data.	processor to This archite	perform	the wavelet
is very general in that it all special encoding methods to accommodates the serial natu for different wavelet kernels, multiplexing for fast operatio which uses acousto-optic m insertion into the system. Th modulators and fixed masks We provide the result of a sin	or most general and lows a large class o accommodate the accommodate the and makes most effin. The processor is odulators and lase the architecture is no which are the basis mulation of the opti	l efficient oper of analyzing v bipolar nature eadout, has the ficient use of w s based on a tri er diodes as a t limited by rea s for many cu ical processor	ation. This p wavelet kerned ability to be avelength-, sj ple product p means of h quiring the us rrent wavelet to show its po	rocessor els, does elet kerne easily rep patial-, ar rocessor sigh throus to of 2-D to processo otential pe	architecture not require el, naturally programmed ad temporal- architecture ughput data spatial light or concepts. erformance.
 is very general in that it all special encoding methods to accommodates the serial natu for different wavelet kernels, multiplexing for fast operatio which uses acousto-optic m insertion into the system. Th modulators and fixed masks We provide the result of a size 20. DISTRIBUTION/AVAILABILITY OF ABSTRACT CXUNCLASSIFIED/UNLIMITED	or most general and ows a large class accommodate the re of sensor data re and makes most eff n. The processor is odulators and lase the architecture is no which are the basis mulation of the opti-	efficient oper of analyzing v bipolar nature eadout, has the ficient use of w s based on a tri er diodes as a t limited by re- s for many cu ical processor (21 ABSTRACT SI Unclassi	ation. This p wavelet kerne e of the wave ability to be avelength-, sp iple product p means of h quiring the us rrent wavelet to show its po	cation parameters of the second secon	artitions the architecture not require el, naturally programmed ad temporal- architecture ughput data spatial light or concepts. erformance.

Contents

I

Fi	igures	iv
1	Introduction	5
2	Background 2.1 Wavelet distributions 2.2 Wavelet Optical Processor Implementation 2.3 Image-based Wavelet Processor 2.4 Spectral-based Wavelet Processor	5 6 9 11
3	Progress to date	15
4	Future Plans	17
A	OSA Presentation Viewgraphs	18

DTIC QUALITY INSPECTED 3

.

Acces	sion For	
NTIS	GRA&I	ſ
DTIC	TAB	ā
Unann	ounced	
Justi	fluation_	
By Distr	ibution/	
Avai	lability	Godes
Dist	Avail and Special	1/or L
0 - 1		
N '		
1		

List of Figures

1	Wavelet transform processor based on time-integrating triple product	
	processor architecture	10
2	Wavelet transform processor which can produce multiple parallel scales	
	via wavelength multiplexing	10
3	Time integrating Fourier transform wavelet processor	12
4	Time integrating wavelet processor based on Fourier transform inter-	
	ferometric processor	12
5	Time multiplexed wavelet processor	13
6	Spatial multiplexed wavelet processor	14
7	Wavelength multiplexed wavelet processor	14
8	Partitioning of the spatial spectrum to generate a modulated $sin(x)/x$	
	analyzing wavelet	16
9	Wavelet time-integrating optical processor simulation output for mod-	
	ulated $sin(x)/x$ wavelet with point target input scene	16

1 Introduction

This document reports the progress to date for the optical wavelet transform processor program. The program started in June 1993. The activities that occurred during the first quarter of the program can be summarized as follows: 1) the program kickoff briefing was given at ONR on 2 June 1993; 2) a simulation of the output of the wavelet transform optical processor has been constructed with initial outputs generated; 3) a paper entitled "Optical time-integrating wavelet transform processor" was prepared and presented at the Annual Optical Society of America Meeting in Toronto, Canada on 5 Oct.; 4) design modifications of the support electronics to the real-time hybrid optical processor to be used in this study were planned. Section 2 will summarize the basic technology used in the optical wavelet transform processor. Section 3 will discuss the first quarter accomplishments of the program. Section 4 will outline the next quarter plans of the program. Lastly, the viewgraphs used in the OSA presentation will be included as an appendix in this report.

2 Background

2.1 Wavelet distributions

A new representation of information that has garnered considerable recent interest is the wavelet distribution of data. This distribution analyzes the local variation of signals (e.g. temporal waveforms, images, etc.) through a set of analyzing functions commonly called wavelets. These analyzing functions are each scaled versions of a basic function called the "mother wavelet." The wavelet distribution, $T_s(r, a)$, is obtained through a correlation between the input data and each wavelet as

$$T_s(r,a) = |a|^{-1/2} \int s(\eta) h\left(\frac{\eta - r}{a}\right) d\eta = h(r,a) * s(r), \tag{1}$$

or by incorporating the scale into the signal as

$$T_{s}(r,a) = |a|^{1/2} \int s(a\eta)h(\eta - r)d\eta = h(r') * s(r',a)$$
(2)

where s(r) is the input signal, h(r, a) is the analyzing wavelet at scale a, r' = r/aand * denotes correlation. Note that for input spatial images we will use the notation $s(\bar{r}) = s(x, y)$. In this instance the wavelet distribution of $s(\bar{r})$ is a four dimensional representation denoted as $T_s(\bar{r}, \bar{a})$ with $\bar{a} = (a_x, a_y)$.

The distribution of the correlations between the input signal and the entire set of wavelets constitutes a decomposition (exact in the limit) of the signal into how fast the signal is changing ("scale") and where it is changing ("space"). The wavelet distribution is also known as a space (time)-scale distribution. In this regard, the wavelet distribution is closely coupled to the general class of time-frequency distributions which try to depict a signal in terms of its local spectrum [2]. A similar class of distributions for time-scale has been proposed which closely mirrors the formulation for time-frequency [3]. It has also been shown that one can derive members of the time-scale class of distributions through an appropriate operation on members of the time-frequency class [3]. An oft cited example is the wavelet transform being a smoothed version of the Wigner distribution function.

2.2 Wavelet Optical Processor Implementation

As noted in Section 2.1, the wavelet distribution of an input image is a 4-D representation of the 2-D function. This added dimensionality incurs some difficulty for optical implementations due to their inherent 2-D nature. Most of the successful work in the real-time implementation of time-scale or time-frequency distributions of signals have been applied to temporal 1-D signals (whose representation is then 2-D) where the 2-D nature of optical processors can be applied naturally. For a 4-D representation, new degrees of freedom must be found in the optical processor which can be exploited. Examples of these degrees of freedom are wavelength, polarization, spatial multiplexing, angular multiplexing and time.

The basic implementation that we are pursuing in this study is a hybrid-optical system based on a time-integrating architecture. This optical architecture is based on synergistic use of optical and electronic componentry to maximize performance. The basic elements of the optical system are laser diodes, acousto-optic spatial light modulators, electronic solid state cameras, and the basic triple product processor optical architecture [4]. We feel that this implementation is the most naturally synergistic with imaging sensors and affords the most general capabilities of wavelet transform processors based on optical technology. The reasons that a time integrating framework are most suitable are:

- Imaging systems (e.g. FLIR, CCD cameras, SAR) perform their data readout in a sequential manner. Formulating a processor which operates on the data as it is read-out reduces processing latency. In this case the input image $s(\bar{r})$ becomes a time sequential data stream as $s(t) = s(x, y)\delta(x - n\Delta xt - m\Delta yT)$.
- ERIM's hybrid-optical systems are based on acousto-optic technology. This technology allows the use of a general class of analyzing wavelets and allows for bipolar operation in a natural manner. No encoding must be made to accommodate the bipolar nature of the analyzing wavelet.
- Hybrid-optical systems have been extensively studied and implemented. Their packaging potential (size, weight, power) has been assessed and have been shown to be superior to digital electronic systems [5].
- Hybrid-optical systems provide another degree of freedom (time) which can be combined with space, angle, and wavelength for best overall performance.

The hybrid-optical time-integrating approach can be contrasted with other methods of producing the wavelet transform of 2-D inputs [6, 7, 8, 9, 10]. These approaches are based upon the use of 2-D spatial light modulators (SLM) for both the input and, in many cases, the wavelet kernels. These systems are typically only amenable to using one extra degree of freedom (spatial multiplexing, angle multiplexing, etc.) in their design and cannot be reprogrammed (different wavelet kernel) on the fly. In many of these approaches the wavelet kernel is transformed into a frequency domain spatial filter such that the traditional 4f coherent optical processor can be used.

These filters can be angularly multiplexed and/or spatially multiplexed. Unfortunately, when multiplexed in this manner, the system is "hardwired" only to those wavelet scales. In this situation, the total number of scales that can be used is defined by the number of filters that can be multiplexed. For angular multiplexing [7], the number of filters that can be used is defined by the dynamic range of the holographic recording media. This is typically limits the number of scales to 5-6. For spatial multiplexing [6], the space-bandwidth product (SBP) of the SLM limits the number of scales and the SBP of the input image. Either a very small number of scales can be used or very small SBP input images. Grey scale two-dimensional SLMs are not very amenable to temporal multiplexing. When binary wavelets (Haar) are used, magneto-optic devices can be brought to bear [8]. These architectures suffer from the need to encode the bipolar nature of the wavelets, however. Other architectures rely on e.g. shadowcasting approaches [9] which require techniques such as polarization encoding to accommodate the bipolar wavelet kernel. Lastly, there are techniques [7] that rely on the physical motion of a lens or filter wheel for operation which is a distinct drawback for remote, real-time operation.

In the next two subsections, we will describe two optical architectures for wavelet transform processing that we are evaluating for application suitability. The first architecture analyzes image data produced by an optical camera, FLIR, etc. These sensors normally use a serial readout of their detector elements. The second architecture operates on spatial spectral data. This type of processor is most suited for sensors which measure the far field distribution of scenes (e.g. SAR). This processor operates directly on the spatial spectral data produced by the sensor (also in a sequential manner) and produces the wavelet decomposition of the scene.

2.3 Image-based Wavelet Processor

The basic optical architecture that we will employ in the image based wavelet transform processor is the triple product processor defined as

$$R(\tau_1, \tau_2) = \int u(t) v^*(t - \tau_1) x(t + \tau_2) dt$$
(3)

and shown in Figure 1. In this architecture, a separable wavelet kernel

$$h(\bar{r}) = h_1(x)h_2(y)$$
 (4)

is inserted into the two acousto-optic cells as

$$v^*(t - \tau_1) = h_1(t - x) \tag{5}$$

$$x(t + \tau_2) = h_2(t - y)$$
 (6)

and the input signal is inserted into the laser diode as

$$u(t) = s(at). \tag{7}$$

This decomposition mirrors the form of the wavelet transform as written in Equation 2. The selection of the scale of the wavelet transform is defined by the rate at which the input data is read into the optical system. Recall that it is the relative scale between the wavelet kernel and the input signal that is being analyzed. The scale of the wavelets remain the same and are repeatedly inserted into the AO cell. The selection of multiple parallel scales is accomplished via a wavelength multiplexed multichannel system where each scale occupies a separate wavelength as shown in Figure 2. Lastly, since the analyzing wavelets are inserted into the AO cells, any bipolar wavelet can be easily accommodated.



Figure 1: Wavelet transform processor based on time-integrating triple product processor architecture



Figure 2: Wavelet transform processor which can produce multiple parallel scales via wavelength multiplexing

2.4 Spectral-based Wavelet Processor

The data for aperture synthesis systems, such as for SAR and for magnetic resonance imaging (MRI), is generated as a serial stream of samples that fills a 2-D Fourier transform space (i.e. spatial spectral space) of the desired image. Wavelet processing of this kind of data can be expressed by

$$T_s(\bar{r},\bar{a}) = \mathcal{F}_{2D}\{S(\bar{f})H^*(\bar{f},a)\}$$

$$\tag{8}$$

where \bar{f} is the spatial spectral space position vector, \bar{a} is the scaling position vector, $H(ar{f},ar{a})$ is the Fourier transform of the wavelet $h(ar{r},ar{a}),\,S(ar{f})$ is the spectral data, * represents conjugation, and \mathcal{F}_{2D} is the 2-D Fourier transform operator. We note that position \overline{f} is a function of time encompassing the conversion of the serial data time stream into 2-D spatial space. Thus, the basic processing is to take a 2-D Fourier transform of the product of the indicated terms with wavelet scale as an independent parameter. The basic processing technique is illustrated in Figures 3 and 4. Figure 3 shows the processing block diagram and Figure 4 shows the optical implementation using a 2-D Fourier Transforming Interferometric Processor. The input serial signal is electronically multiplied and then inserted into the optical portion of the processor as a 2-D formatted spatial input signal. The output wavelet transform is continually being formed as the data flows into the processor. For the setup shown in Fig. 4 the various scaled versions of the wavelet would be generated by repeating the operation for each desired scale. For faster operation the system can be multiplexed in time, space, or wavelength to form a set of scaled wavelet transforms during one data acquisition time.

For time multiplexing we depend on the processor being much faster than required for a single wavelet transform. Each section is processed and the output is summed to the appropriate memory section by buffering sections of the input signal and interlacing the sections after being multiplied by the appropriate wavelets sections. (See Fig. 5.) Thus, all the different scaled wavelet transforms are being formed



Figure 3: Time integrating Fourier transform wavelet processor



Figure 4: Time integrating wavelet proces or based on Fourier transform interferometric processor



Figure 5: Time multiplexed wavelet processor

in a cyclic fashion such that all the wavelet transforms have been formed during one data acquisition time.

Spatial multiplexing can be done as illustrated in Fig. 6. It depends on the processor having excess space-bandwidth product capability. By encoding each wavelet on a different carrier and multiplying the incoming data with the sum of the encoded wavelets the various scaled wavelet transforms come out at different positions in the output. In this case all the wavelet transforms are being formed simultaneously.

Wavelength multiplexing is illustrated in Fig. 7. In this case the technique depends on the fact that the optical portion of the processor can run in parallel for different wavelengths. Each one of these wavelength channels produces its own different scaled wavelet transform. Thus, all the wavelet transforms are formed simultaneously.

Of course, mixed multiplexing using some combination of the three techniques is also possible to increase the processing throughput even further.







Figure 7: Wavelength multiplexed wavelet processor

3 Progress to date

We have simulated the output of the spectral-based wavelet transform optical processor. All of the salient operations have been incorporated into the simulation. Examples of these operations are: multiplying the spatial spectrum data of a scene by the transform of the wavelet kernel (equation 8); modulating the resultant data by a carrier and adding a bias to the signal; performing the cosine transform on the spectral data; simulating the detection process incorporating photon noise; demodulating the detected output into a complex image.

The input scene that was analyzed consisted of a set point targets, each with a random phase $(\phi \sim U[-\pi,\pi])$, in the configuration of a Σ . The spatial spectrum of the scene was then obtained. This spatial spectrum was treated as the collected data from a synthetic aperture radar. The spatial spectrum of the scene was then processed in subsets in azimuth as shown in Figure 8. The partitioning of the spatial frequency aperture in azimuth is equivalent to analyzing the scene via a modulated sin(x)/xfunction as the mother wavelet. The scales of the analyzing wavelet were chosen to be equivalent to an octavel decomposition of the input scene. An octavel decomposition is the basis for \mathbf{n} ost discrete wavelet decompositions of signals. The simulation shown in Figure 9 shows the time-integrating nature of the optical processor whereby each "image" is a sample of the post detection digital summation memory of the processor (see section 1.4). As the spatial spectrum is being inserted into the system and processed the partial result is contained in the post detection memory. The state of that memory at any particular time corresponds to a specific analyzing wavelet scale. The figure shows variation in the signature as a function of scale. In addition, the figure shows that a very high dynamic range output can be attained when the system is photon noise limited. These results were presented at the Optical Society of America annual meeting in Toronto, Canada on 5 Oct., 1993 [11].



n service. Na service

Figure 8: Partitioning of the spatial spectrum to generate a modulated sin(x)/x analyzing wavelet.



$\rho = 1/2 \rho_c$



р = 1/64 р_с

Figure 9: Wavelet time-integrating optical processor simulation output for modulated sin(x)/x wavelet with point target input scene.

4 Future Plans

The simulation of the time-integrating wavelet transform optical processor will be further enhanced to incorporate detector read noise and the use of two dimensional wavelet ke ______ These enhancements are simple extensions of the current capabilities. In addition, the pre- and post-optical electronic systems of the hybrid processor will be reconfigured such that modulation by the wavelet kernel can be accomplished and the post detection memory can be sampled such that multiple scenes analyzed at different scales can be easily read out. It is anticipated that a full demonstration of the optical processor will be held in the fourth quarter of this program.

A OSA Presentation Viewgraphs

OPTICAL TIME-INTEGRATING WAVELET TRANSFORM PROCESSOR

Nikola S. Subotic, Carl C. Aleksoff

Environmental Research Institute of Michigan Advanced Concepts Division Ann Arbor, MI 48113-4001 P.O. Box 134001

Sponsored by Office of Naval Research (Dr. William Miceli)



TOPICS

- Wavelet distributions background
- Time integrating optical processor implementation
- Image based processor
- Spectral based processor
- Simulation results
- Summary and conclusions



WAVELET DISTRIBUTIONS

• Can be formulated in the "spatial" or "spectral" domains of the signal

$$T_s(x, y, a_x, a_y) = (a_x a_y)^{-1/2} \int s(\eta,
ho) h\left(rac{\eta - x}{a}, rac{
ho - y}{a_y}
ight) d\eta d
ho$$

 $= (a_x a_y)^{1/2} \mathcal{F}_{2D} \{S(f_x, f_y) H^*(f_x, f_y, a_x, a_y)\}$

- where \mathcal{F}_{2D} is the Fourier transform operation, $S(f_x, f_y)$, $H(f_x, f_y, a_x, a_y)$ are the Fourier transforms of the signal s and the analyzing wavelet ћ.

• Scale can be incorporated either in the signal or the analyzing wavelet

$$T_s(x, y, a_x, a_y) = (a_x a_y)^{1/2} \int s(a_x \eta, a_y \rho) h(\eta - x, \rho - y) d\eta d\rho$$

IMAGE-BASED WAVELET	the triple product processor	ncoded into the input signal $u(t) = s(at)$ which is inserted	; kernel must be separable $h(\bar{r}) = h_1(x)h_2(y)$ and inserted
PROCESSOR	$I_{1}(t)$ $I_{2}(f,a')$ $I_{1}(t)$ $I_{2}(f,a')$ $I_{1}(t)$ $I_{2}(f,a')$ $I_{1}(t)$ $I_{1}(t,\tau_{2})$ $I_{1}(t,\tau_{2})$ $I_{2}(t)$ $I_{1}(t,\tau_{2})$ $I_{2}(t)$ $I_{2}(t,\tau_{2}) = \int u(t)v^{*}(t-\tau_{1})x(t+\tau_{2})dt$ Detector Array	aser diode	wo acousto-optic cells
ERIM	• Based on	• Scale is en into the la	• Analyzing into the tw



WAVELENGTH MULTIPLEXING

- Produces multiple scales in parallel
- Each channel has the input signal inserted at a different rate
- The signals provided by the different sources will not interact and will be processed independently.





)

d on the Fourier data of the signal and the analyzing wavelet $T_s(x, y, a_x, a_y) = (a_x a_y)^{1/2} \mathcal{F}_{2D} \{S(f_x, f_y) H^*(f_x, f_y, a_x, a_y)\}$	/ aperture synthesis systems (synthetic aperture radar-SAR, letic resonance imaging-MRI) generate spectral data	H*(Ē(t),ā)) ↓	S(F(t))-X FT PROCESSOR Signal Wavelet Transform		
	• Based on the Fourier data of the signal and the analyzing wavelet $T_s(x, y, a_x, a_y) = (a_x a_y)^{1/2} \mathcal{F}_{2D} \{S(f_x, f_y) H^*(f_x, f_y, a_x, a_y)\}$	 Based on the Fourier data of the signal and the analyzing wavelet T_s(x, y, a_x, a_y) = (a_xa_y)^{1/2} F_{2D}{S(f_x, f_y)H[*](f_x, f_y, a_x, a_y)} Many aperture synthesis systems (synthetic aperture radar-SAR, magnetic resonance imaging-MRI) generate spectral data 	 Based on the Fourier data of the signal and the analyzing wavelet T_s(x, y, a_x, a_y) = (a_xa_y)^{1/2} F_{2D}{S(f_x, f_y)H[*](f_x, f_y, a_x, a_y)} Many aperture synthesis systems (synthetic aperture radar-SAR, magnetic resonance imaging-MRI) generate spectral data H[*](f(t),ā) 	• Based on the Fourier data of the signal and the analyzing wavelet $T_s(x, y, a_x, a_y) = (a_x a_y)^{1/2} \mathcal{F}_{2D} \{S(f_x, f_y) H^*(f_x, f_y, a_x, a_y)\}$ • Many aperture synthesis systems (synthetic aperture radar-SAR, magnetic resonance imaging-MRI) generate spectral data H*($\overline{f}(t), \overline{a}$) $H^*(\overline{f}(t), \overline{a})$ $S(\overline{f}(t)) \rightarrow \bigotimes_{F_1} \sum_{F_2} \sum_{F_1} \sum_{T_s(\overline{f}, \overline{a})} \sum_{F_1} \sum_{F_2} \sum_{F_1} \sum_{T_2} \sum_{F_1} \sum_{T_2} \sum_{F_1} \sum_{F_2} \sum_{F_2} \sum_{F_2} \sum_{F_1} \sum_{F_2} \sum_{F_1} \sum_{F_2} \sum_{F_2} \sum_{F_1} \sum_{F_2} \sum$	• Based on the Fourier data of the signal and the analyzing wavelet $T_{s}(x, y, a_{x}, a_{y}) = (a_{x}a_{y})^{1/2} \mathcal{F}_{2D} \{S(f_{x}, f_{y}) H^{*}(f_{x}, f_{y}, a_{x}, a_{y})\}$ • Many aperture synthesis systems (synthetic aperture radar-SAR, magnetic resonance imaging-MRI) generate spectral data H^{*}(\tilde{f}(t), \tilde{a}) • $H^{*}(\tilde{f}(t), \tilde{a})$ • $H^{*}(\tilde{f}(t), \tilde{a}$

-





FOURIER TRANSFORM INTER-FEROMETER



- Interferometer based on Modified Kosters Interferometer (MKI) architecture
- Acousto-optic cells used as scanners (controls spatial frequency)
- Data (Fourier coefficient) inserted into laser diode





PROCESSOR IMPLEMENTATION TIME-INTEGRATING OPTICAL

- Based on triple product processor architecture using acousto-optic modulators, laser diodes, and solid state imaging cameras
- Very general architecture
- partitions the optical/electronic workload for general and efficient operation

25

- allows for a large class of analyzing wavelet kernels e.g. bipolar, complex valued
- naturally accommodates the serial nature of sensor data readout easily reprogrammed for different kernels
- makes most efficient use of wavelength-, spatial- and temporalmultiplexing for fast operation



SUMMARY AND CONCLUSIONS

- Use optical processing when real-time is required and numerical accuracy is not crucial
- Hybrid electronic/optical processors make best use of strengths of each technology
- Time integrating processors naturally accommodates sensors with time serial readout
- Time integrating processors can be expanded via wavelength multiplexing
- Time integrating processors can be configured for either spectral or spatial based wavelet expansion of images

References

- C. K. Chui, Wavelets: A Tutorial in Theory and Applications, (Academic Press, New York), 1992.
- [2] L. Cohen, "Time-frequency Distribution-A Review," Proc. IEEE, 77, No. 7, July, 1989.
- [3] O. Rioul, and P. Flandrin, "Time-scale Energy Distributions: A General Class Extending Wavelet Transforms," IEEE Trans. Sig. Proc., 40, No. 7, July, 1992.
- [4] P. Kellman, "Time Integrating Optical Signal Processing," Opt. Eng., 19, 370, May-June, 1980.
- [5] N. S. Subotic, C. C. Aleksoff, and A. M. Tai, "Comparison of Hybrid-Optical and Digital Computers for Real-Time 2-D Fourier Transform Based Operations," Proc. SPIE, 960, June 1988.
- [6] Y. Sheng, et. al., "Optical Wavelet Transform," Opt. Eng., 31, Sept. 1992.
- [7] X. Yang, et. al., "Optical Haar Wavelet Transforms of Binary Images," Opt. Eng., 31, Sept. 1992.
- [8] T. Burns, et. al., "Optical Haar Wavelet Transform," Opt. Eng., 31, Sept. 1992.
- Y. Sheng, et. al., "Optical N⁴ Implementation of a Two-dimensional Wavelet Transform," Opt. Eng., 31, Sept. 1992.
- [10] Y. Li, and Y. Zhang, "Coherent Optical Processing of Gabor and Wavelet Expansions of One- and Two-dimensional Signals," Opt. Eng., 31, Sept. 1992.
- [11] N.S. Subotic, and C. C. Aleksoff, "Optical time-integrating wavelet transform processor," Presented at the 1993 Optical Society of America Annual Meeting, 4-8 Oct. 1993, Toronto, Canada.