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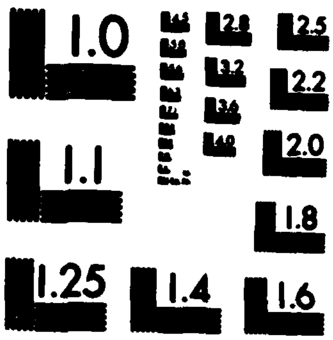

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OPTICAL DATA PROCESSING

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-Our research concerns optical data processing for missile guidance and target recognition. It uses pattern recognition techniques with an increasing use of knowledge base, inference machine and associative processor techniques. Our Year 2 work addresses devices (the liquid crystal television), Kalman filters, intrinsic features, iconic filters, and symbolic processors. These all represent quite novel optical processing concepts. Our work also concerns new architectures and concepts such as: relational graph processors, optical linear discriminant processors, model-based optical processors, hierarchical symbolic optical correlators, and optical associative processors.

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symbolic correlators, optimal distortion invariant filters, intrinsic filters, iconic filters, relational graphs, optical linear discriminant functions, model-based processors, associative processors, symbolic hierarchical correlators.

Table of Contents

ABSTRACT AND SUMMARY

Our research concerns optical data processing for missile guidance and target recognition. It uses pattern recognition techniques with an increasing use of knowledge base, inference machine and associative processor techniques. Our Year 2 work addresses devices (the liquid crystal television), Kalman filters, intrinsic features, iconic filters, and symbolic processors. These all represent quite novel optical processing concepts. Our work also concerns new architectures and concepts such as: relational graph processors, optical linear discriminant processors, model-based optical processors, hierarchical symbolic optical correlators, and optical associative processors.

1. INTRODUCTION

The first year of this grant (1 October 1984 - 1 October 1985) produced much good work. This period was followed by an unsupported research period. By the end of our second year (January - December 1986) of this effort, we are again on track, having overcome various problems associated with no funding for one semester. Chapter 2 provides a summary overview of our calendar year 1986 research progress. Subsequent chapters detail each aspect of this research.

We are phasing out all feature extraction research and have now completed all student projects in this area. This work is summarized in Chapters 5 and 6. We have also ceased our Kalman filter research (since no Eglin Air Force Base funds were available to transition support of this work). Chapter 4 notes our final effort in this area. Our hierarchical symbolic processing concept is noted in Chapter 12. It utilizes correlation filters and thus we are continuing research in this area. This work is detailed in Chapters 7-11. After discussions with AFOSR, we have made a considerable redirection of our research effort toward optical computing rather than pattern recognition. Chapters 13-17 highlight five new research directions originated in 1986. These include: relational graph processors, model-based processors, and analysis of the Hopfield associative memory, new nearest neighbor data matrix associative processors, and distortion-invariant associative processors. These represent four new optical approaches to advanced computing.

In 1986, the Principal Investigator (PI) was quite active with various invited papers on numerous topics: the IEEE Spectrum article (August 1986), an SPIE Institute Series paper on scene analysis [5], an Optics News special issue article [7]. He also has been most active in various conference organizations. He was Chairman of a hybrid image processing conference (April 1986), Chairman of a digital image processing session (January 1986), Chairman of a set

of six conference on robotics (October 1986), plus provided an invited paper at the ICALEO'86 conference. We have thus expended considerable effort to expose our work and AFOSR research to a quite wide community.

2. SUMMARY AND OVERVIEW

We now provide a summary and overview of our 1986 research progress and highlight the contents of Chapters 3-17 which detail 15 different aspects of our research.

2.1 SPATIAL LIGHT MODULATORS (SLMs) (Chapter 3, Liquid Crystal Television Correction)

SLMs represent the critical element in most optical processors. The liquid crystal television (LCTV) emerged in late 1985 as a low-cost and viable optical SLM. Our work [8] on this device included practical remarks about bias voltage selection and polarization reorientation, the demonstration of interpolation on the device by single sideband filtering, and the selection of beam balance ratio spatial filtering techniques using such a sampled input SLM. Our primary contribution was the use of a new phase conjugate hologram correction technique to correct for the phase nonuniformity of the device. This allows its use in a space integrating correlator, as we experimentally demonstrated.

2.2 FACTORIZED KALMAN FILTER (KF) ALGORITHM (Chapter 4)

This chapter concludes our AFOSR work in this area [15]. ONR/SDI support for this may allow us to continue some of this work. This 1986 work involves a new parallel vectorized and factorized KF algorithm. This is very suitable for optical processing, since it requires a reduced accuracy optical processor. This is achieved since the algorithm does not entail processing full matrices, nor does it involve square root and other time-consuming operations. We have detailed how this algorithm can be employed on an optical processor.

2.3 FEATURE EXTRACTION (MOMENTS, FOURIER TRANSFORMS AND HARTLEY TRANSFORMS) (Chapters 5 and 6)

This work concludes our intrinsic (or feature extraction) OPR (optical pattern recognition) research. We feel that optics has a considerable role in low-level vision, where the input data rate is the highest and where the number of operations per input data pixel or point is the largest. One thrust of this research has been to provide more features from one optical feature space. This is attractive since separate optical architectures are then not necessary for each desired feature space. Chapter 5 considers an optical Fourier transform feature space (this is the simplest feature space that one can optically generate). We show in this chapter how the moments can be obtained from this feature space [16]. We also provide a new digital filtering technique and algorithm to aid calculation of moments from Fourier coefficients [17]. Chapter 5 summarizes this work [18] and conference paper [19] provides new simulation results on detector area effects and other results using this feature space.

The basic architecture involves an optical Fourier transform system with and without a linear $\underline{x}$ mask present. The Fourier transform produced by this system is sampled, and an approximate derivative is digitally produced by a differentiating finite impulse response filter using a new algorithm and techniques. The associated moments are then assembled from these samples. Techniques to achieve this with and without a linear $\underline{x}$ mask are noted. In total, 21 samples of the Fourier transform are used to produce 21 moments. For the case of symmetric inputs, we find the odd order moments above third order are in error by over 7%. For asymmetric inputs (these are typical of most real objects), all moments up to eighth-order are accurate within 2%. We found that the sampling of this system was optimal at $1/4L$ (where L is the size of the input). We also found that as the digital filter length increases, the number of usable moments also increases (with a filter length of 15 being adequate for all moments up to order 5). Detector area effects were also considered (such as area sampling, which was found to be a small negligible error compared to the filter length effect). Concerning detector dynamic range, we found that a 16-bit A/D converter was adequate. Our noise analysis showed that approximately 0 dB input plane SNR could be tolerated. Our initial results showed very good separation of different tool parts for different rotated and translated versions of these input images.

We also provided a journal paper [4] in 1986 that detailed the computer generated hologram fabrication of a wedge ring detector with experimental data on this system included.

We have also [24] detailed how one can obtain the Hartley transform from the Fourier transform and how one can obtain moments from the Hartley transform (Chapter 6). This implementation technique is quite attractive since no additional mask is now required. This arises because the Hartley transform is real. The Hartley transform has other attractive properties as well. These are discussed in the aforementioned reference. We have also developed a new algorithm to recursively calculate all moments from the n-derivatives of the Hartley transform at the origin. This thus represents additional work associated with producing various feature spaces from and on the same optical processor.

Paper [25] discusses other uses for this system and proves that all geometrical moments can be calculated recursively from the partial derivatives near the origin in the Hartley transform intensity pattern.

2.4 APPROACHES TO LARGE-CLASS ANALYSIS PROBLEMS (Chapters 7 and 12)

As noted in Chapter 1, our approach we consider for advanced processors involves a hierarchical symbolic correlator. The basic concepts of such a processor [21] are advanced in

Chapter 12. They involve the use of multiple hierarchical levels of different advanced distortion-invariant filters. This yields a unique symbolic processor, whose outputs are the spatial representation of the input data for different correlation filters.

In 1986, various aspects of iconic filters were studied and several new concepts emerged. Chapters 7-10 detail these results. In Chapter 7, we analyze the simplest filter (an equal correlation peak (ECP) filter) assuming Gaussian and exponential image models for the correlation functions [22] with attention to the large-class problems. Various effects (space bandwidth product, in-plane scale and rotation distortion, noise, and the number of training images) are investigated in terms of the output SNR for an ECP projection synthetic discriminant function (SDF). Quantitative data on all issues are advanced. Similar results are obtained for both image models. This is encouraging, since the results should thus be extendible to more general models and to real imagery. We also find that as the number of training images increases, the best SNR decreases and the worst-SNR increases. We also find larger differences between the best and worst-case SNR as the space bandwidth product increases. These results provide us with many useful guidelines:

1. increases in the training set size (beyond some value N) will cause little improvement,

2. more training set images are useful for larger space bandwidth product images,

3. smaller space bandwidth product images may yield higher SNR outputs when the number of training images N is limited.

4. for each N selected, there is an optimum space bandwidth product.

We plan to employ these results in our future hierarchical symbolic processor research.

Our 1000 class OCR (optical character recognition) results [14] represent the first case study data on a large class optical processor. The first multi-level and multi-filter optical processor studies are included in this work. Also included are the first attention to the effects of a large number of object classes (as occurs in the advanced inference and optical computing and

AI (artificial intelligence) processors using knowledge bases, that we consider). These results should be most attractive and appropriate for advanced optical AI, symbolic, and optical computing architectures.

2.5 NEW ICONIC FILTERS FOR HIERARCHICAL PROCESSORS (Chapter 8-10)

Chapter 8 details our minimum variance SDF iconic filter [23]. This theoretical study advances the case of a linear combination filter and when such a filter is best, and the performance of the conventional SDF in the presence of colored (real) noise (versus its performance in white Gaussian noise). It also advances cases of a nonlinear discriminant function. We constrain the integrated intensity of the filter in all images to be unity (rather than assuming a linear combination filter). For the case of white noise, we found that the filter that minimizes the output noise variance is the linear combination ECP projection SDF that we previously developed. In colored noise, the optimal filter is a different linear combination filter function. The inverse of the covariance matrix C of the noise is required to obtain this optimal SDF. This covariance matrix inverse is not always easily obtained. Approximations to it are one of various future research topics possible. The suboptimality of the conventional ECP-SDF in colored noise is also quantified in this chapter.

We also devised [1] new Fisher and mean square error (MSE) filter functions (Chapter 9). These filters use a reduced orthogonal basis function set and conventional pattern recognition synthesis techniques. They are fabricated such that conventional parameters for pattern recognition are optimized. This is attractive from a theoretical standpoint. These filters also offer promise for fabricating reduced dynamic range and special (i.e. binary and phase only) filter functions.

As noted at the outset, these various filter functions are planned to play a significant role in our advanced hierarchical correlator and iconic filter as well as symbolic processor architectures and algorithms (Chapter 12).

New correlation filters and peak to sidelobe ratio (PSR) filters (Chapter 10) that are superior to the original projection SDF filters were also detailed [11]. The projection filters constrain only the peak value of the correlation function. The correlation filters control the shape of the correlation function and the PSR filters provide easily detectable correlation peaks. These three filters are employed in our hierarchical correlator architecture and concept [3,22].

2.6 COMPUTER GENERATED HOLOGRAM (CGH) FILTER SYNTHESIS (Chapter 11)

This task study concerns the number of amplitude and phase levels required in a correlation filter [20]. Large class problems are considered. We find that phase-only filters are inferior for discrimination and in large class cases. Several amplitude levels are found to significantly improve performance.

2.7 OPTICAL ARTIFICIAL INTELLIGENCE (Chapters 13-17)

These chapters advance four new concepts for advanced optical computing. This work involves a relational graph processor [2,12]. This also includes the concept of an optical linear discriminant function, techniques to organize a knowledge base, and the concept of a parallel data base search (Chapter 13). Our work has also advanced the first optical use of a model-based representation [6] (Chapter 14) for input objects. Advances in graphics can be expected to make this approach most attractive, especially for advanced large data base cases. It is very attractive in terms of computer memory requirements, filter generation for correlators and for associative processor memory systems as detailed elsewhere (Chapter 12). We conducted detailed initial studies [26] that noted severe storage problems with the Hopfield associative memories and that the nature of the input data to such processors was quite restrictive and was thus not the general vectors required for pattern recognition (Chapter 15). We then advanced a data matrix nearest neighbor associative processor [27] that is preferable (Chapter 16). Our final contribution [13] has involved distortion-invariant associative processors (Chapter 17). This work includes the first quantitative data on such processors, new synthesis techniques for these processors and new synthesis techniques to improve their memory capacity. One general paper on this work [9] was published in 1986. Attention to optical processing techniques for range image data were also advanced [10]. Several invited papers at the January 1987 SPIE conference on this area will be available shortly.

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