Latency-Information Theory and Applications. Part II: On Real-World Knowledge Aided Radar

Erlan H. Feria
The College of Staten Island (CSI) of the City University of New York (CUNY)
Department of Engineering Science and Physics
2800 Victory Blvd, Staten Island, New York, 10314
e-mail:feria@mail.csi.cuny.edu, website:http://feria.csi.cuny.edu

ABSTRACT

In this second of a multi-paper series latency-information theory (LIT), the integration of information theory with its time dual, i.e., latency theory, is successfully applied to DARPA's knowledge aided sensor signal processing expert reasoning (KASSPER) program. LIT encapsulates the concept of the time dual of a lossy source coder, i.e., a lossy processor coder. A lossy processor coder is a replacement for a signal-processor. This lossy processor coder is faster, simpler to implement, and yields a better performance than the original signal-processor when the processor input appears in a highly compressed-decompressed lossy fashion. In particular, a *lossy* clutter covariance processor (CCP) architecture is investigated that has successfully replaced KASSPER's originally advanced *lossless* CCP and enabled its SAR imagery prior knowledge to be highly compressed-decompressed. This result is illustrated with a typical SAR image which is compressed-decompressed by a factor 8,172. Using this image and under severely taxing environmental disturbances outstanding detections are achieved with the lossy CCP. Furthermore, this result is derived with a lossy CCP that is at least five orders of magnitude faster and significantly simpler to implement than the corresponding lossless CCP whose SINR detection performance is nevertheless unsatisfactory. As a final comment it is also observed that LIT illuminates biological system studies since it provides a lossy mechanism that explains how outstanding detections may be arrived at by biological systems that use highly lossy compressed prior knowledge, e.g., when a human expertly detects a face seen only once before even though that face cannot be accurately described prior to such new viewing.

Keywords: space-time dual, time dual, latency, latency theory, information, latency-information theory, sourced-space, motion-time, processing-time, retention-space, bits, bors, lossy processor, processor ectropy, source entropy, sensor consciousness, channel capacity, knowledge aided, radar, intelligent system, DARPA, KASSPER, biology

1. INTRODUCTION

As stated in the first of this multi-paper series [6], and I quote,

"A real-world problem whose high performance is attributed to its use of an intelligent system (IS) is knowledge-aided (KA) airborne moving target indicator (AMTI) radar such as found in DARPA's knowledge aided sensory signal processing expert reasoning (KASSPER) [1]-[2] program. The IS's intelligence, or prior knowledge, is clutter synthetic aperture radar (SAR) imagery and its intelligence processor (IP), or on-line computer, is the associated clutter covariance processor. Unfortunately, however, the excellent signal to interference plus noise ratio (SINR) radar performance achieved directly depends on satisfying prohibitively

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expensive storage and computational requirements. The former 'storage' problem is easily addressed by using a highly efficient lossy source coding technique, e.g., a minimum mean squared error (MMSE) predictive-transform (PT) source coder [3] that compresses a typical SAR image by several orders of magnitude: a MMSE PT source coder is used rather than the JPEG2000 standard [4] since the PT coder outperforms JPEG by at least 5dB in this application [5]. Yet, a lossy source coder compressor seriously compromises the SINR radar performance. Thus one seeks the replacement of the clutter covariance processor with a processor that is better matched to highly compressed SAR imagery."

In this second of a multi-paper series a replacement for a clutter covariance processor (CCP) is advanced using as a guide latency theory, the discovered time dual for information theory [6]. In particular, latency theory and information theory are unified to form a latency-information theory (LIT) which encapsulates the concept of a *lossy* processor [6]. A lossy processor is a processor that may be better matched to a highly lossy version of a *lossless* signal-processor's input than the lossless signal-processor itself. More specifically for our radar application, a *lossy* CCP architecture is investigated that replaces the *lossless* CCP, or intelligent system, and enables its input SAR imagery prior knowledge to appear in highly compressed lossy form. This result is illustrated with a typical SAR image that has been compressed by a factor of 8,172. Using this image and under severely taxing environmental disturbances outstanding detections are achieved with the lossy CCP. Furthermore, this occurs while the lossy CCP is at least five orders of magnitude faster and much simpler to implement than the corresponding lossless CCP whose SINR detection performance is unsatisfactory when its input appears highly compressed-decompressed. As part of the interpretation of these results it is also observed that LIT illuminates biological system studies since it provides a lossy mechanism that explains how outstanding detections may be arrived at by biological systems that use highly lossy compressed prior knowledge, e.g., when a human expertly detects a face seen only once before even though that face cannot be accurately described prior to such new viewing.

The paper begins with a succinct overview of latency-information theory. This theory combines the communication system in information theory with the recognition system in latency theory in a single system. The paper continues with a discussion of the CCP used in KASSPER's knowledge aided AMTI radar system. The paper then discusses the advanced lossy CCP and shows some simulation results.

2. LATENCY-INFORMATION THEORY

Refer to Fig. 1 where a recognition system is combined with a communication system to yield a recognition-communication system. In [6] a detailed description is given of the communication system and recognition system subsystems appearing in this figure. Nevertheless a succinct summary of these subsystems is advanced next. While a communication system is composed of a channel, source-coder, channel-coder and motion-coder, the time dual of a communication system, i.e., a recognition system, is composed of a sensor, processor-coder, sensor-coder and retention-coder. A channel is the medium through which knowledge must be space dislocated. A source-coder (encoder/decoder) replaces an inefficient signal-source with one yielding a smaller sourced-space penalty in *b*inary dig*its* (*bits*) units. A channel-coder identifies the necessary overhead-knowledge for a more accurate transmission of the sourced-space. A motion-coder is a transmitter/receiver device that space-dislocates (or moves) knowledge with the *smallest motion-time* possible [7]. A recognition system, as defined in [6], uses prior-knowledge about a signal-processor's input to enable the sensing of its output by a processing-time limited sensor when the fastest possible signal-processor replacement cannot achieve this task. A sensor is the time dual of a channel and motivates the required time-dislocation of the processing-time to an earlier time via the use of prior-knowledge. The processor-coder is the time dual of the source-coder and replaces the signal-processor with one yielding a smaller processing-time penalty in *b*inary operat*ors* (*bors*) units. The sensor coder is the time dual of the channel-coder and its purpose is to identify the necessary prior-knowledge for an earlier beginning of the processing-time. A retention-coder is a write/read device that time-dislocates (or retains) knowledge with the *smallest retention-space* possible [7]. Information-theory uses the sourced-space performance bound penalties of source-entropy $\boldsymbol{H}$ and channel-capacity $\boldsymbol{C}$ to guide the design of channel and source integrated (*CSI*) coders. On the other hand, latency-theory uses the processing-time performance bound penalties of processor-ectropy $\boldsymbol{K}$ and sensor-consciousness $\boldsymbol{F}$ to guide the design of sensor and processor integrated (*SPI*) coders. While the bounds $\boldsymbol{H}$ and $\boldsymbol{C}$ are ruled by the uncertainty associated with the passing of time, the bounds $\boldsymbol{K}$ and $\boldsymbol{F}$ are ruled by the certainty associated with the configuration of space. Finally, the laws of physics are used in the design of motion-coders and retention-coders. While the laws of motion are used in the design of motion-coders, in the third of this multi-paper series [7] a space dual for the laws of motion is discovered, therein named the laws of retention, that directly addresses the design of retention-coders. In [7] in the same spirit as for information theory and its time dual latency theory, a *motion-ectropy* $\boldsymbol{A}$ performance bound in second units is defined for the design of motion-coders and a *retention-entropy* $\boldsymbol{N}$ performance bound in cubic meters is defined for the design of retention-coders. Furthermore, while the motion-ectropy $\boldsymbol{A}$ is ruled by the certainty associated with the configuration of space, the retention-entropy $\boldsymbol{N}$ is ruled by the uncertainty associated with the passing of time.

In this paper the discussion will be limited to the use of the source-entropy $\boldsymbol{H}$ and the processor-ectropy $\boldsymbol{K}$ to guide us in the evaluation of the performance of the advanced lossy CCP. Hence we will only define these two measures of performance next for ease of reference.

The *source-entropy* $\boldsymbol{H}$ is defined by

$$\boldsymbol{H} = \sum_{i=1}^{U} P[o_i] I_S[o_i] \quad \text{in } \textit{bits} \text{ per } \mathbf{X} \in \{o_1, \ldots, o_U\} \tag{2.1}$$

where $\mathbf{X}$ is a source output discrete random variable with U outcomes $\{o_i\}$, $I_S[o_i]$ is the *source-information* advanced by the source outcome o_i and given by

$$I_S(o_i) = \log_2(1/P[o_i]) \text{ in } \textit{bit}\text{s per } o_i \tag{2.2}$$

with the probability $P[o_i]$ being a measure of o_i's uncertainty, which is in turn driven by the passing of time [8]. A source-coder's design is then approached using $\boldsymbol{H}$ as a performance bound. In particular, the source coder rate R_{SE} in bits per $\mathbf{X}$ units reflects a *sourced-space penalty* incurred by the source coder. Thus when R_{SE} is greater than or equal to the source-entropy $\boldsymbol{H}$ and less than or equal to the source rate R_S, i.e.,

$$\boldsymbol{H} \le R_{SE} \le R_S \tag{2.3}$$

we say that the source coder is lossless and when R_{SE} is smaller than $\boldsymbol{H}$ we say that the source coder is lossy.

On the other hand, the *processor-ectropy* $\boldsymbol{K}$—the time dual of the source-entropy $\boldsymbol{H}$—is defined by

$$\boldsymbol{K} = \max(L_P(y_1),..,L_P(y_J)) \quad \text{in } \textit{bors} \text{ per } \mathbf{y} = [y_1, \ldots, y_J] \tag{2.4}$$

where $\mathbf{y}$ is a processor vector output with J elements $\{y_i\}$, $L_P[y_i]$ is the *processor-latency* of y_i which is defined as the minimum processing-time that is needed to obtain y_i after the original signal processor is redesigned subject to implementation processor constraints $\{C[y_i]\}$ [6]. Thus

$$L(y_i) = \mathrm{f}(C[y_i]) \quad \text{in } \textit{bors} \text{ per } y_i \tag{2.5}$$

with $\mathrm{f}(C[y_i])$ indicating that $L(y_i)$ is a function of $C[y_i]$. The constraint $C[y_i]$ is the time dual of probability $P[o_i]$ and is driven by a *configuration of space certainty*, e.g., the 'certain' occupancy-space in m^3 occupied by NAND gates. The design of a processor-coder is then approached using $\boldsymbol{K}$ as a performance bound. **A** lossless processor-coder is the time-dual of a lossless source-coder. It has a R_{PC} achievable, i.e.,

$$\boldsymbol{K} \le R_{PC} \le R_P \tag{2.6}$$

It is also ideal when R_{PC}=$\boldsymbol{K}$ and is equivalent to the signal processor when R_{PC}=R_P. A lossy processor-coder is the time-dual of a lossy source-coder. It has a R_{PC} that is not achievable, i.e.,

$$0 \leq R_{PC} < \boldsymbol{K} \tag{2.7}$$

but is faster and simpler to implement than a lossless one.

3. KASSPER'S KNOWLEDGE AIDED CLUTTER COVARIANCE PROCESSOR

KASSPER's knowledge aided CCP is found inside the AMTI of the radar system of Fig. 2. An array of N antenna elements radiates M consecutive pulses during a coherent-pulse-interval (CPI). These pulses are echoed back at some distance away, more than a thousand meters, from a front clutter range-bin. The range-bin is composed of an even number of cells N_C where the boundary line between cells $N_C/2$ and $(N_C+2)/2$ is investigated to determine if a moving target appears there. When N_C is large, say 256, cell 1 and cell N_C have a bore-sight angle θ of approximately -90° and 90°, respectively, i.e., $\theta(1) \approx -90^{o}$ and $\theta(N_C) \approx 90^{o}$. Furthermore, the antenna-gains $\{g_i\}$ associated with these cells are found from

$$g_i(\theta(K)) = G^f \left| \frac{\sin\left\{ N\pi \frac{d}{\lambda}(\sin(\theta(i)) - \sin(\theta(K))) \right\}}{\sin\left\{ \pi \frac{d}{\lambda}(\sin(\theta(i)) - \sin(\theta(K))) \right\}} \right|^2 \quad \text{where } i = 1,...,N_c \tag{3.1}$$

where θ $(K=(N_C+1)/2) = 0^{o}$, d is the antenna inter-element spacing, λ is the operating-wavelength, and G^f is the global front antenna-gain [9].

The prior-knowledge (or intelligence) system embedded in the AMTI consists of a prior-knowledge signal source in cascade with a CCP. The prior-knowledge source contains clutter range-bins in the form of SAR-imagery. In Fig. 3A a typical 4 Megabytes SAR image is shown. Since the prior-knowledge storage needs are overwhelming in a real-world scenario [1]-[2], a key practical problem is the design of a highly lossy but useful source coder for its replacement such as a MMSE PT source coder [5]. Fig. 3B displays the compressed-decompressed image that is derived when a MMSE PT source coder compresses the image of Fig. 3A by a factor of 8,172. The CCP, on the other hand, evaluates on-line the 256^2 complex elements of clutter covariance matrix

$$\mathcal{C}_c^f = \sum_{\mathbf{i=1}}^{N_C} x_{\mathbf{i}} g_{\mathbf{i}} \mathbf{c}_{\mathbf{i}} \mathbf{c}_{\mathbf{i}}^{\mathbf{H}} \tag{3.2}$$

where: a) $\mathbf{x}=[x_1,\ldots,x_{Nc}] \in \mathcal{R}^{Nc}$ is the real clutter source power vector; b) $\mathbf{g}=[g_1,\ldots,g_{Nc}] \in \mathcal{R}^{Nc}$ is the real antenna gain vector; c) $\mathbf{c}_i \in C^{NM}$ is the complex steering column vector of the i-th range-bin cell; and d) $\mathbf{c}_{\mathbf{i}}^{\mathbf{H}}$ is the transposed and complex conjugate of $\mathbf{c}_i$.

In turn, $\mathcal{C}_c^f$ is then used to derive the weighting vector $\mathbf{w} \in C^{NM}$ that multiplies the AMTI-vector-input $\mathbf{z}(t_i)$+$\mathbf{s}(t_i)$ where $\mathbf{z}(t_i) \in C^{NM}$ is an interference plus noise vector and $\mathbf{s}(t_i) \in C^{NM}$ is the moving-target steering-vector. This multiplication yields

$$y(t_i+\mathrm{T}_w)=\mathbf{w}(t_i+\mathrm{T}_w)^{\mathrm{H}}(\mathbf{z}(t_i)+\mathbf{s}(t_i)) \tag{3.3}$$

or

$$y(t_i+\mathrm{T}_w)=\mathbf{w}(t_i+\mathrm{T}_w)^{\mathrm{H}}\mathbf{z}(t_i) \tag{3.4}$$

depending on whether the moving target is present or not, respectively. T_w is the processing-time used by the AMTI to evaluate **w**. The AMTI decides on the basis of the magnitude of its complex scalar output $y(t_i+T_w)$, which of the two outputs, i.e., (3.3) or (3.4), is the one more likely to have occurred.

The expression relating **w** to $\mathcal{C}_c^f$ is

$$\mathbf{w}=\mathcal{C}^{-1}\mathbf{s} \tag{3.5}$$

where $\mathcal{C}$ is the covariance of **z**, i.e., $\mathcal{C}=E[\mathbf{z}\mathbf{z}^H]$. Expression (3.5) results from the maximization of the signal to interference-plus-noise ratio (SINR)

$$\text{SINR}=\mathbf{w}^H\mathbf{s}\mathbf{s}^H\mathbf{w}/\ \mathbf{w}^H\mathcal{C}\mathbf{w} \tag{3.6}$$

where $\mathbf{w}^H\mathbf{s}\mathbf{s}^H\mathbf{w}$ is the power of the signal, **s**, part of (3.3) and $\mathbf{w}^H\mathcal{C}\mathbf{w}$ is the power of the interference-plus-noise, **z**, part of (3.3). To model $\mathcal{C}$ in a real-world scenario a covariance matrix tapers (CMTs) formulation [9] is used

$$\mathcal{C}= \{(\mathcal{C}_c^f+\mathcal{C}_c^b)\text{O}(\mathcal{C}_{RW}+\mathcal{C}_{ICM}+\mathcal{C}_{CM})\}+\{\mathcal{C}_J\text{O}\mathcal{C}_{CM}\}+\mathcal{C}_n \tag{3.7}$$

where $\mathcal{C}_c^b$, $\mathcal{C}_n$, $\mathcal{C}_J$, $\mathcal{C}_{RW}$, $\mathcal{C}_{ICM}$, and $\mathcal{C}_{CM}$ are *NM*x*NM* dimensional covariance complex matrices and the symbol O denotes a Hadamard product or element by element multiplication. These covariances correspond to: $\mathcal{C}_c^b$ to back-clutter; $\mathcal{C}_n$ to thermal-white-noise; $\mathcal{C}_J$ to jammer; $\mathcal{C}_{RW}$ to range-walk; $\mathcal{C}_{ICM}$ to internal-clutter-motion; and $\mathcal{C}_{CM}$ to channel-mismatch. The covariances $\mathcal{C}_{RW}$, $\mathcal{C}_{ICM}$, and $\mathcal{C}_{CM}$ are called CMTs. Since the on-line computation burden of $\mathcal{C}$ is mostly due to $\mathcal{C}_c^f$ (3.2) and taxes heavily the available computational resources, the signal-processor evaluating (3.2) must then be replaced with the fastest possible processor, either lossless or lossy, that can also handle highly compressed prior-knowledge (Fig. 3B). This problem is thus one of designing a new processor that compresses the processing-time of a signal-processor with its output either being the same as that of the original signal-processor (the lossless case) or different (the lossy case).

4. A NOVEL CLUTTER COVARIANCE PROCESSOR ARCHITECTURE

A novel lossy CCP coder architecture is now advanced (see Fig. 4) for replacement of the lossless front clutter covariance matrix $\mathcal{C}_c^f$ (3.2) and its effectiveness demonstrated while in the presence of severely taxing environmental disturbances. This highly lossy power-centroid CCP coder has a sensor coder in cascade with a source coder providing a highly lossy prior knowledge input. The main task of the sensor coder is to advance as prior knowledge range bins obtained from a SAR image. Each range bin consists of 16 averaged consecutive rows of a SAR image (see Fig. 3) from which the front clutter source power vector input $\mathbf{x}=[x_1,\ldots,x_{Nc}]$ is derived. The source coder, on the other hand, is a highly lossy MMSE PT source coder [5] that, for instance, generates Fig. 3B for a compression factor of 8,172.

The lossy power centroid processor coder consists of a power centroid extractor (PCE) in cascade with a predicted clutter covariance (PCC) selector. The PCE derives from the front range-bin clutter power vector

$$\mathbf{xOg}=[x_1g_1 \quad x_2g_2 \quad \cdots \quad x_{N_C}g_{N_C}] \tag{4.1}$$

its power $P(\mathbf{x}\text{O}\mathbf{g})$ and centroid $C(\mathbf{x}\text{O}\mathbf{g})$ thus

$$P(\mathbf{xOg})=\sum_{i=1}^{N_C}x_ig_i\ , \tag{4.2}$$

$$C(\mathbf{xOg})=\sum_{i=1}^{N_C}ix_ig_i\Big/\sum_{i=1}^{N_C}x_ig_i=\sum_{i=1}^{N_C}ix_ig_i\,/\,P(\mathbf{xOg})\,. \tag{4.3}$$

The PCC-selector, on the other hand, quantizes the $P(\mathbf{x}\text{O}\mathbf{g})$ and $C(\mathbf{x}\text{O}\mathbf{g})$ as follows

$$Q[P(\mathbf{x}\mathrm{O}\mathbf{g})] = \begin{cases} QP_2, & QP_1 < P(\mathbf{x}\mathrm{O}\mathbf{g}) \le QP_2 \\ QP_1, & P_{Min} \le P(\mathbf{x}\mathrm{O}\mathbf{g}) \le QP_1 \end{cases} \tag{4.4}$$

$$QP_1 = \frac{P_{Min} + P_{Max}}{2}, \qquad QP_2 = P_{Max} \tag{4.5}$$

$$Q[C(\mathbf{x}\mathrm{O}\mathbf{g})] = \begin{cases} QC_3, & (QC_2 + QC_3)/2 < C(\mathbf{x}\mathrm{O}\mathbf{g}) \le N_C \\ QC_2, & (QC_1 + QC_2)/2 < C(\mathbf{x}\mathrm{O}\mathbf{g}) \le (QC_2 + QC_3)/2 \\ QC_1, & 1 \le C(\mathbf{x}\mathrm{O}\mathbf{g}) \le (QC_1 + QC_2)/2 \end{cases} \tag{4.6}$$

$$QC_1 = QC_2 - D, \qquad QC_2 = (N_C + 1)/2, \qquad QC_3 = QC_2 + D \tag{4.7}$$

where QP_i and QC_i are quantization levels for $P(\mathbf{x}\mathrm{O}\mathbf{g})$ and $C(\mathbf{x}\mathrm{O}\mathbf{g})$, respectively. P_{Max}, P_{Min}, and D are found making use of the prior-knowledge (Fig. 3B) and the antenna gain (3.1) with $\theta(K=(N_C+1)/2)=0^{\circ}$. The resultant quantization levels are then used to select from a memory device one of six PCCs. The PCCs are derived off-line from

$$\mathbf{PCC}_{k,j} = X_{k,j} \sum_{i=1}^{N_C} g_i(\theta(QC_j))\mathbf{c}_i\mathbf{c}_i^{\mathbf{H}} \tag{4.8}$$

$$X_{k,j} = \frac{QP_k}{\sum_{i=1}^{N_C} g_i(\theta(QC_j))}. \tag{4.9}$$

From expressions (4.8) and (4.9) it is noted that $\mathrm{PCC}_{k,j}$ is a function of QP_k and the gains $\{g_i(\theta(K = QC_j))\}$ (3.1) (these gains match the antenna-pattern of Fig. 2 when j=2). The on-line processing-time of the lossy power/centroid processor coder is mostly due to the PCE of (4.2) and (4.3).

A comparison of (4.2) and (4.3) with (3.2) reveals that the lossy power/centroid processor-coder improves by several orders of magnitude the processing-time and implementation complexity needed for the evaluation of (3.2) since (3.2) requires x_i to be multiplied by the g_i weighted 256x256 complex steering matrix $g_i\mathbf{c}_i\mathbf{c}_i^{\mathbf{H}}$ while (4.2) and (4.3) do not. Thus a factor of $2\mathrm{x}256^2$=131,072 on-line processing-time saving is derived, as well as a significantly reduced implementation complexity. In this comparison it has been assumed that (3.2) is evaluated using an ideal lossless processor-coder satisfying three on-line computational constraints (clearly other constraints can be used depending on the available computational resources). They are: 1) the N_C=256 complex matrices $\{x_i g_i\mathbf{c}_i\mathbf{c}_i^{\mathbf{H}}\}$ appearing in (3.2) are simultaneously evaluated by 256 sub-processors; 2) the aforementioned $2\mathrm{x}256^2$=131,072 basic multiplications associated with each complex matrix $x_i g_i\mathbf{c}_i\mathbf{c}_i^{\mathbf{H}}$ are performed by a sub-processor in a sequential fashion; and 3) the sum of the 256 matrices $\{x_i g_i\mathbf{c}_i\mathbf{c}_i^{\mathbf{H}}\}$ leading to $\mathcal{C}_c^f$ is implemented with 255 matrix additions. Thus the ectropy $\boldsymbol{K}$ exhibited by this ideal lossless processor-coder is given by $\boldsymbol{K} = 131{,}072b_M + 255b_A$ bors/ $\mathcal{C}_c^f$ where b_M is the number of bors per multiplication and b_A is the number of bors per addition. It should be noted that when finding the previous expression for $\boldsymbol{K}$ it was both assumed that the latency associated with each complex scalar element of $\mathcal{C}_c^f$ is the same and any time-delays introduced by memory read/write operations are reflected in the b_M and b_A values. Furthermore, since the number of additions leading to $\boldsymbol{K}$ is significantly smaller than the number of multiplications and it is also assumed that b_M>>b_A it follows that $\boldsymbol{K}$ can be approximated by $131{,}072b_M$

bors/ $\mathcal{C}_c^f$. On the other hand, the evaluation of the lossy power-centroid processor-coder output $\hat{\mathcal{C}}_c^f$ of Fig. 4 leads to an approximate processor-coder rate R_{PC} of b_M bors/ $\hat{\mathcal{C}}_c^f$ where the availability of appropriate parallel-processing computational resources was assumed. Thus an estimated on-line processing-time improvement of $\boldsymbol{K}/R_{PC}$ = 131,072 results from the use of our lossy processor-coder.

5. SIMULATION RESULTS

The SINR radar performance derived with the lossy power centroid processor coder is investigated next making use of the radar parameters of Table 1 [9]-[10]. Also 64 simulation range-bins, each 256 dimensional, are derived from Fig. 3A and Fig. 3B by averaging 16 adjacent-rows. For each range-bin the SINR is determined for normalized Doppler from -1/2 to 1/2 where the Doppler-sign conveys the direction of the moving target with respect to the AMTI-platform and its magnitude informs us about the relative speed of the moving target with respect to that of the AMTI-platform. In Fig. 5A SINR versus normalized Doppler plots are given for three cases. The first case is the optimum SINR performance plot that results when (3.2) and range-bin #1 of Fig. 3A are used. The second and third cases make use of range-bin #1 from Fig. 3B. An average SINR error (ASE) of 1.04 dBs is derived when using the lossy power centroid processor coder of Fig. 4 and an ASE=4.8-dBs when the lossless (3.2) is evaluated. In Fig. 5B the ASE is plotted versus range-bin number for both the lossless and lossy processor cases where an average ASE improvement of more than 4.5 dBs is achieved when using the lossy power centroid processor coder of Fig. 4. Finally, it is noted, that the lossy processor coder of section 4 can be augmented with the channel coder of Fig. 1 when highly-compressed prior-knowledge is stored in a central-command station and then transmitted to an AMTI [1,2].

6. CONCLUSIONS

The principal revelation of this paper is that information-theory and its discovered time-dual, latency-theory can be unified to form a latency-information theory (LIT) that guides system design as was successfully illustrated in this paper. In addition, LIT can be viewed as a mathematical theory of prior-knowledge (or intelligence) that supervises efficient prior-knowledge (or integrated recognition/ communication) system designs. A highly desirable result surfaced when real-world knowledge-aided radar operating with highly-compressed prior-knowledge only yielded fast and outstanding detections if a *lossy* processor replaced a slower and more complex lossless one. This was the case because the advanced lossy processor coder was significantly better matched to the lossy prior knowledge than the lossless processor coder. This result is enlightening from an engineering perspective and is also consistent with the performance of biological systems that produce swift and excellent detections while in the presence of a highly compressed prior-knowledge environment. For instance, such is the case when a human after a new viewing expertly detects a human face seen only once before, even though that face cannot be accurately described prior to such new viewing [11]. The reader is finally encouraged to refer to the first and third of this multi-paper series [6]-[7] for more discussions on LIT.

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Table 1 Simulation Parameters

a.	Antenna	N = 16, M = 16, $d/\lambda = ½$, $f_r = 10^3$ Hz, $f_c = 10^9$ Hz, $K^f = 4x10^5$ or 56 dBs, $K^b = 10^{-4}$ or -40 dBs,
b.	Clutter	$N_c = 256$, $\beta = 1$, 41 dBs < $10\log_{10}CNR^f$ < 75 dBs, ${}_b\sigma^2_{c,i} = 1$ for all i, $10\log_{10}CNR^b$ = -40 dBs,
c.	Target	$\theta_t = 0^o$
d.	Antenna Disturbance	$\sigma^2_n = 1$, $\theta_{AAM} = 2^o$
e.	Range Walk	$\rho = 0.999999$
f.	Internal Clutter Motion	b = 5.7, $\omega = 15$ mph
g.	Narrowband CM	$\varepsilon_i = 0$ for all i, γ_i for all i fluctuates with a 5^o rms
h.	Finite Bandwidth CM	$\Delta\varepsilon = 0.001$, $\Delta\phi = 0.1^o$
i.	Angle Dependent CM	$B = 10^8$ Hz, $\Delta\theta = 28.6^o$
j.	Sample Matrix Inverse	Lsmi = 8x64=512, $\sigma^2_{diag} = 10$

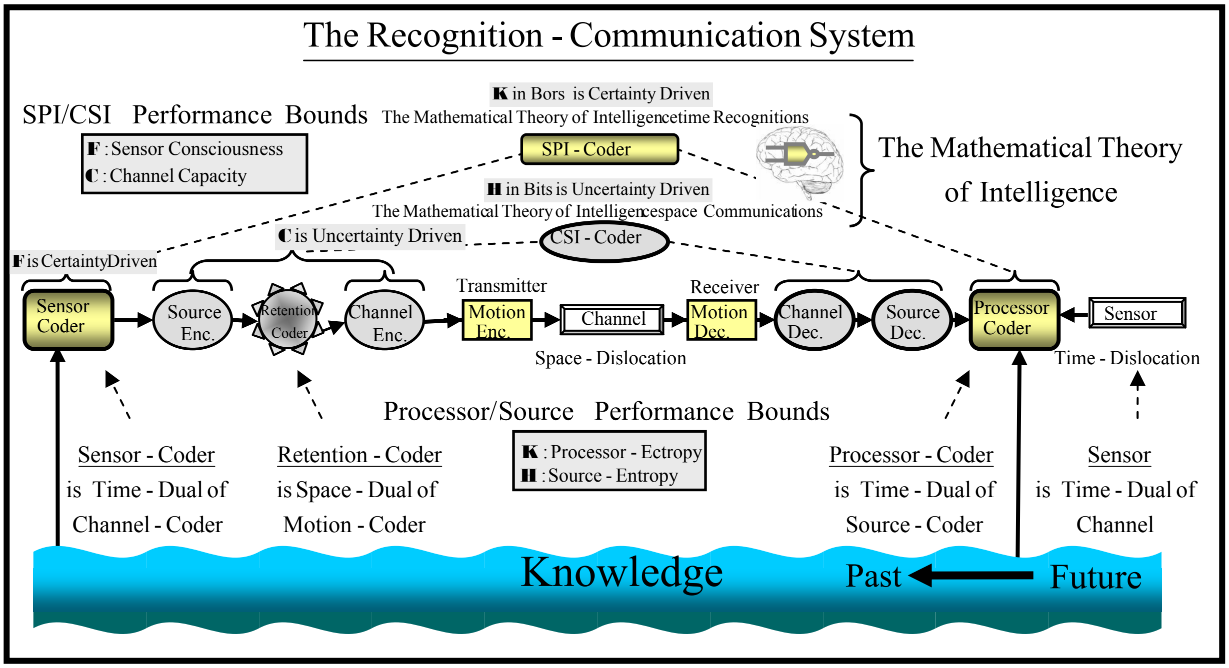

Fig. 1 Latency-Information Theory's Recognition/Communication System

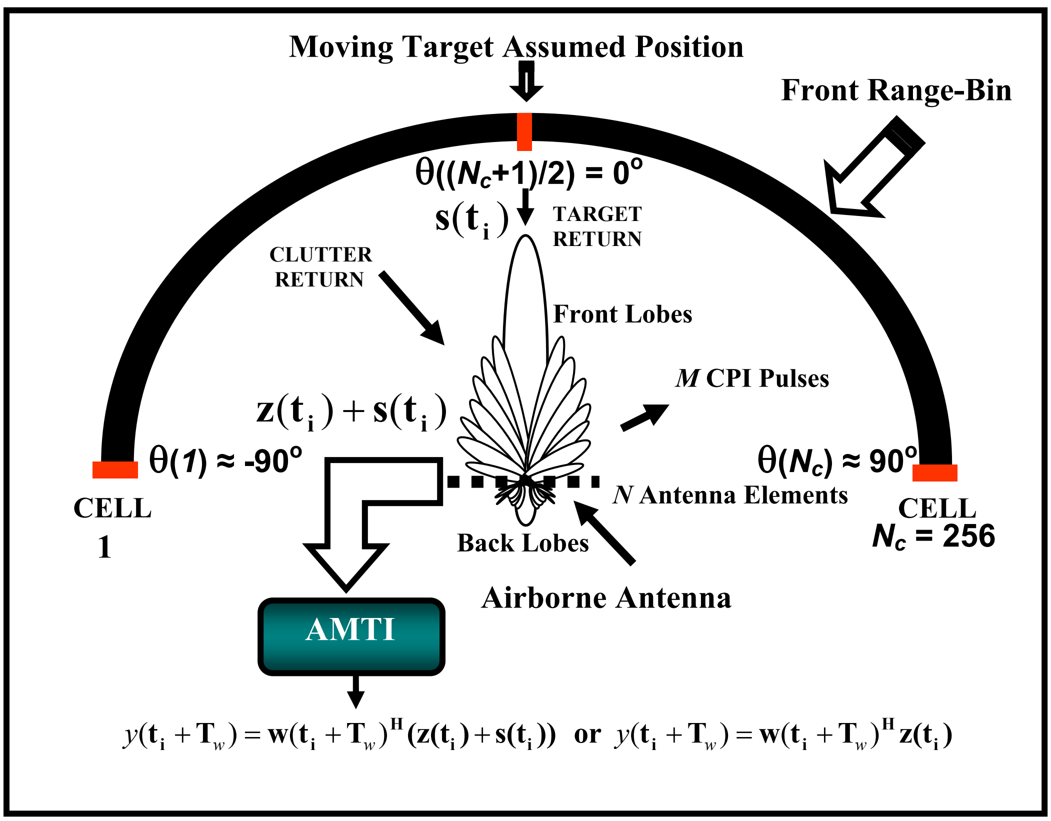

Fig. 2 Airborne Moving Target Indicator Radar System

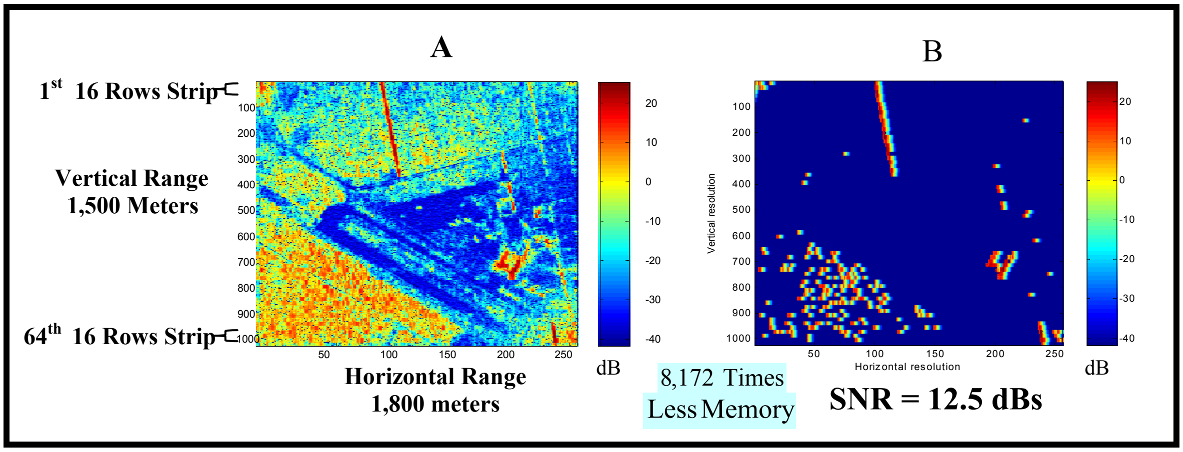

Fig. 3 A) 4 Megabytes SAR Image of Mojave Airport in California
B) 512 Bytes SAR Image Encoded/Decoded With a MMSE PT Source Coder

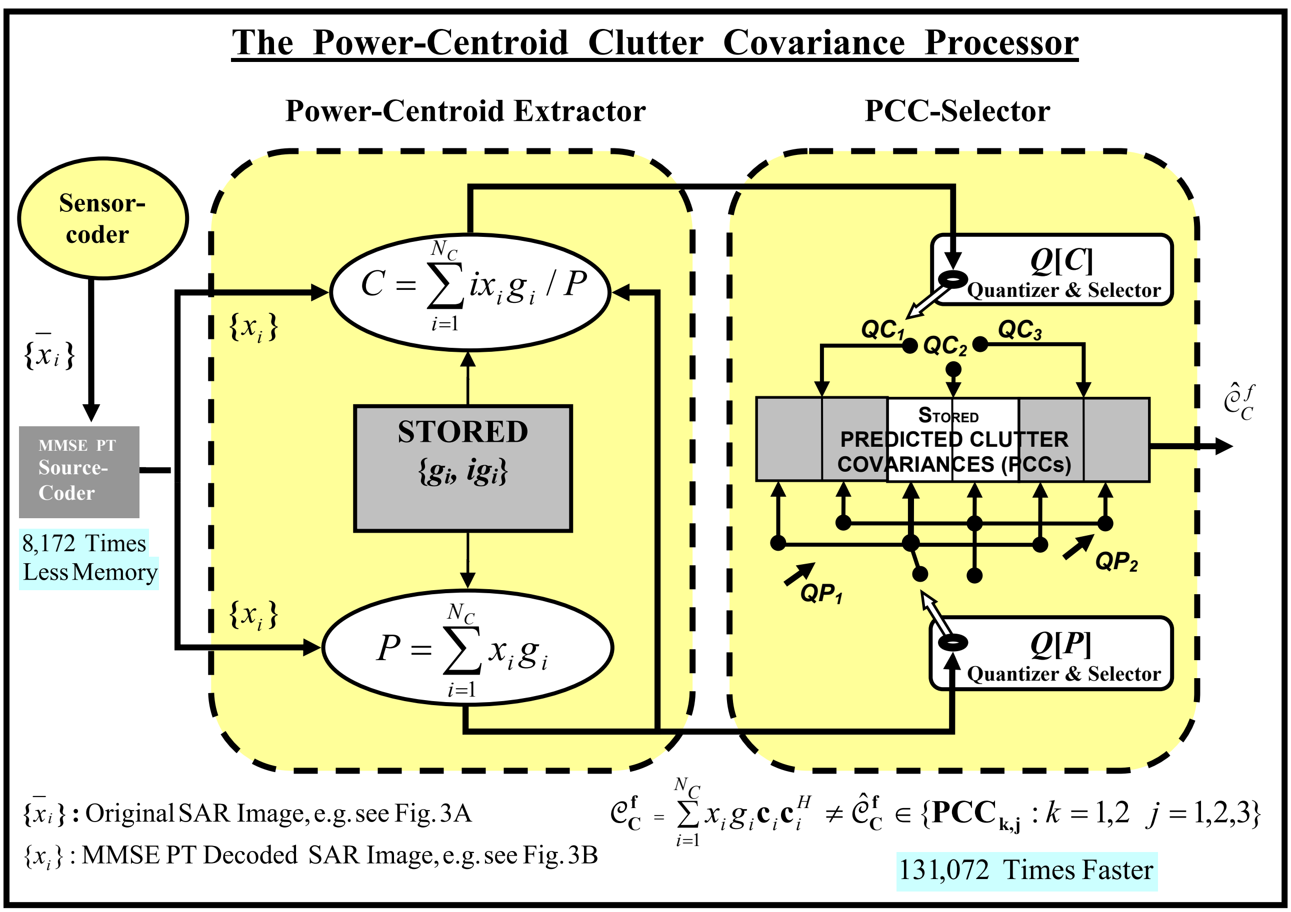

Fig. 4 Lossy Power-Centroid Clutter Covariance Processor

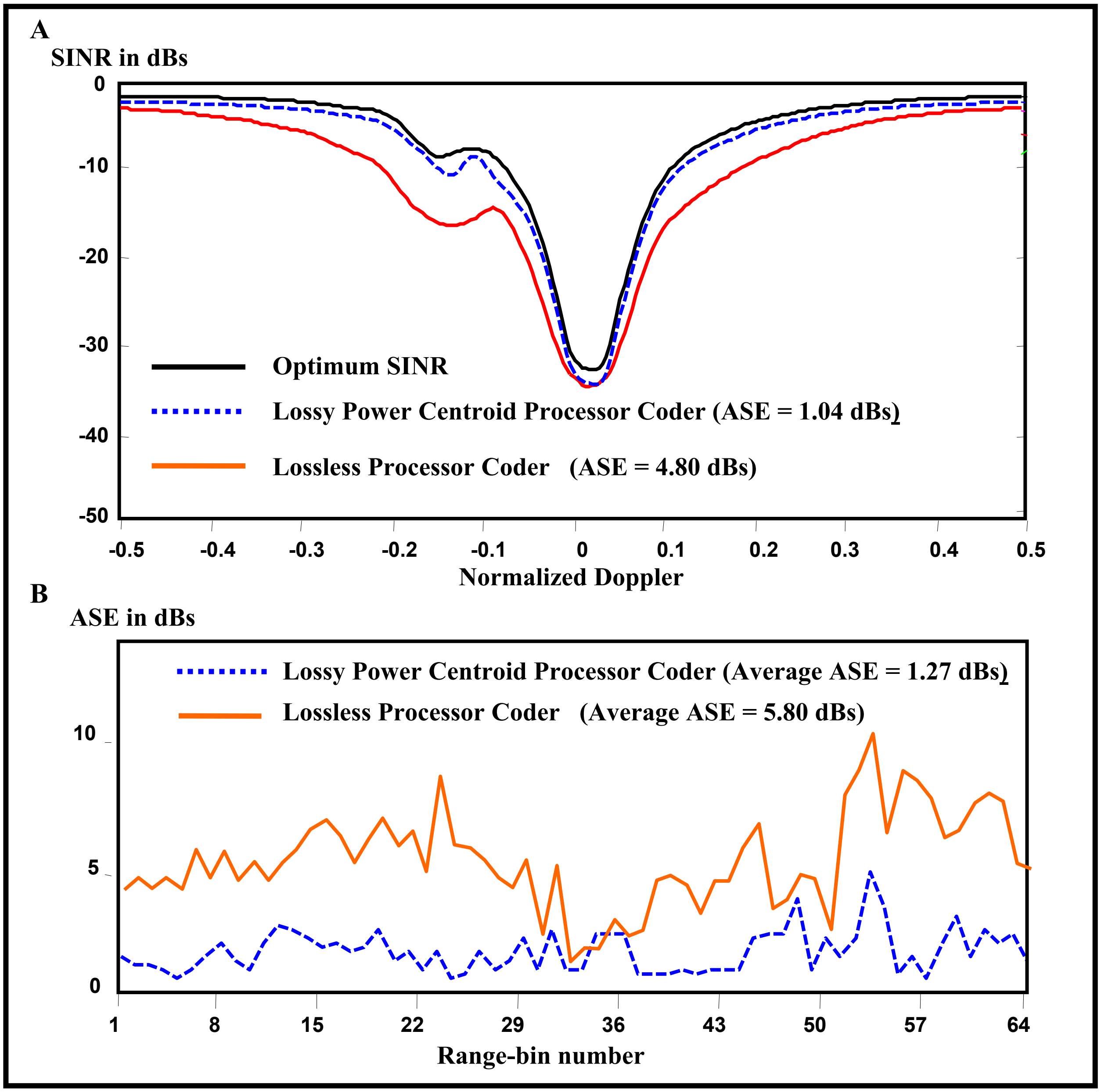

Fig. 5 A) SINR versus normalized Doppler for range bin #1
B) Average SINR error versus range bin number