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An analysis framework for event-based sensor performance

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ABSTRACT

Event-Based Sensors (EBSs) are passive electro-optical (EO) imaging sensors which have read-out hardware that only outputs when and where temporal changes in scene brightness are detected. In the case of a static background and platform, this hardware ideally implements background clutter cancellation, leaving only moving object data to be read out. This data reduction leads to a bandwidth reduction, which is equivalent to increasing spatio-temporal resolution. This advantage can be exploited in multiple ways, using trade-offs between spatial and temporal resolution, and between spatial resolution and field-of-view. In this paper, we introduce the EBS concept and our previous experiments and analysis. We discuss important EBS properties, followed by discussion of applications where the EBS could provide significant benefit over conventional frame-based EO sensors. Finally, we present a method for analyzing EBS technology for specific applications (i.e. determine performance compared to conventional technology). This approach involves abstraction of EBS and conventional imaging technology and provides a way to determine the value of EBSs over conventional imaging technology for facilitating future EBS application development.

Keywords: Event-Based Sensor, Image Science, Performance, Systems Engineering, Modeling and Simulation, Analysis

1. INTRODUCTION TO EBS

The event-based sensor (EBS)[1], is a passive electro-optic (EO) imaging sensor with read-out hardware that outputs asynchronously, only when and where pixel-level temporal changes in scene irradiance are detected. In the case of a moving target and a static background and platform, this sensor ideally implements background clutter cancellation, leaving only moving object data to be read out. When the objective is to detect moving objects, this emulates a conventional frame-based detection technique[2], with the added advantage of increased spatio-temporal resolution[4]. This is because data reduction leads to a bandwidth reduction, which is equivalent to increasing spatio-temporal resolution.

EBS processing can be abstracted with a subtract-and-threshold operation[3], where EBS only outputs when the difference between the current and previous measured log irradiance exceeds a threshold. This log irradiance change can be approximated as a percent irradiance change. While similar operations can be implemented in software with conventional imaging technology, EBS is different in that it is not limited by a fixed frame rate. In other words, the asynchronous output leads to a bandwidth advantage over conventional technology which is discussed throughout this paper.

1.1 Positive EBS features

The EBS has several traits that can be beneficial to an application, including random-access read-out, dynamic range, and low Size, Weight, and Power (SWAP).

Random-access readout is an important feature in EBS; in that it allows EBS to isolate and output quickly from any single pixel on the focal plane which has not recently been read out. This is where we see the primary EBS advantage, as faster read-out can in some instances be traded off for improved application performance. Random-access readout also has the advantage of providing a high temporal resolution timestamp for each event[1]. In other words, the EBS can quickly log the time when a pixel triggers. Random-access readout, by itself, is somewhat unique to EBS, but many cameras have similar dynamic windowing functionality[5].

The EBS also has high dynamic range, with many devices specified at 120dB. We interpret dynamic range as the ratio of maximum and minimum irradiances that can be operated on by the EBS, across the focal plane. It should be noted that

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high dynamic range, by itself, is not unique to EBS. For example, several other cameras can generate images with at least 120dB of dynamic range[6]. While other devices share some performance characteristics with EBS, we see EBS as having a combination of unique capabilities which may improve applications.

An additional benefit of random-access readout is a significant reduction in SWAP. We have observed[4] that EBS can have at least several orders of magnitude bandwidth reduction. This was compared to an equivalent conventional camera running at 100 frames per second. Under specific constraints, this can translate into several orders of magnitude reduction in power required to read-out and process EBS data. The decrease in processing power can be especially useful in SWAP limited systems such as aircraft. Here, avionics-grade processors are SWAP expensive, and often must timeshare between different subsystems. By reducing processor requirements, lower-performance processors may be used, allowing EBS integration in lower-cost systems where conventional EO sensors would be SWAP prohibitive.

1.2 Negative EBS traits

While the EBS has many advantages, which might be applied in valuable ways, current EBS technology has disadvantages including high noise, single-bit irradiance output, reduced scene information, and low sensitivity.

High sensor noise is a significant issue in EBS technology. Other works discuss this noise and what causes it [7, 8]. Examples of recent EBS devices mitigate noise through back-side illumination and additional circuitry[9, 10]. This circuitry adds new capabilities to the focal plane array which reduce noise and increase the maximum bandwidth (data output rate) at the expense of decreased timestamp precision.

Single-bit irradiance contains information on whether an event signifies increased or decreased irradiance. This leads to a decrease in relevant information available to the user, potentially decreasing performance in tasks such as detection and classification. However, EBS models have been built which capture a simultaneous conventional image[11] or directly output the irradiance from a triggered pixel[12]. This might be mitigated by fusing EBS information with conventional imaging sensor information, such as the output from the DAVIS model[11].

The EBS has low sensitivity, often cited at around a 20% change required to register an event in 50% of pixels in an EBS focal plane[10]. This is due to variability in the threshold at each pixel. Because pixels have thresholds tuned in aggregate, and due to non-linear behavior in the tuning circuitry, removing this variability and reducing the sensitivity threshold is difficult. Despite this, prototypes have been built to achieve higher sensitivity[13].

1.3 Performance

An important concept here is performance. We define performance as the capability to complete a specific task, in a specific scenario. Often, performance is quantified with a metric, which can be directly measured, or a composite metric consisting of multiple measurements. An example of a direct metric is focal plane size, where more pixels is often considered an improvement to an imaging system. An example of a composite metric is in target detection, where probability of detection and probability of false alarm are computed simultaneously. Here, performance is seen as the ability to have high detection probability while simultaneously having low false alarm probability.

Often, there are trade-offs in systems, where reconfiguration can maximize a single direct metric's performance, at the expense of other metrics. A single direct metric often implicitly includes other metrics, and as such is often an inaccurate way of measuring overall performance. Because of this, a good performance metric is often a composite metric, as this can take trade-offs into account and give a more holistic view of performance than a single direct metric. Using the example of target detection, a detection camera might have a multi-gigapixel focal plane[26]. However, a large camera has large power requirements, and requires large processing power to read-out and analyze the image. In a SWAP limited system, it would be difficult to justify this camera, despite high performance in focal plane size.

2. EBS APPLICATIONS

Applications of an EBS-based system involve its utilization to accomplish one or more specific task(s). Each application has its own level of complexity. An application can require other, lower-complexity applications to complete a task.

Often, the simpler an application is, the simpler it is to measure performance. As applications become more complex, the difficulty and complexity in demonstrating performance increases. For example, a high-complexity application such as target tracking may require a lower-complexity application such as change detection. For change detection, one way to measure performance is through simple laboratory experiments measuring sensitivity of change detections in a single target. For target tracking, detection performance would likely need to be measured across a range of different scene and target configurations, requiring more complex measurements.

In simple cases, an application's tasks may perform similarly when measured with the same method. Then, by measuring performance on one of the similar tasks, performance is represented for all of the similar tasks. By measuring only once, performance measurement is simplified, at the expense of any differences being ignored. In other words, simplification and abstraction can also lead to decreased metric accuracy. For example, with change detection, a single experiment measuring with single target can predict performance across a wide range of targets. Because of the low complexity of the change detection application, measurements against different targets are expected to provide similar results. With target tracking, performance against one scene/target does not often represent performance against other scene/targets. Because of the higher complexity, target tracking does not abstract as well as change detection, and doing so there will lead to lower-accuracy performance measurements.

In some applications, tasks are similar and can be easily generalized with simple metrics. In others, task performance is sensitive to application parameters, and as such cannot be generalized without sacrificing measurement accuracy. This is important because in simple cases, testing can be a relatively minor part of the development process. In more complex cases, testing can be the most important part of development. Continuing with the target tracking example, change detection often abstracts better than target tracking, as performance here is the sensitivity to irradiance changes. As irradiance is not a target- or scene-specific measurement, it is simple to abstract across many different targets and scenes. In target tracking, the goal is to detect, classify and follow a target. The target has features, and performance with EBS depends on change detection between the background scene and the target, with factors including lighting, pose, weather, and clutter. As this performance is target and scene-specific, with sensitivities to many factors, general performance measurement is complex.

Next, we discuss a few illustrative EBS applications, including prior work and methods of measuring performance. The goal is to understand application complexity and where more rigorous methods are necessary to manage and understand this complexity.

2.1 Computer Vision

Computer vision is a commonly researched EBS application. Researchers investigating EBS for computer vision[14, 15] have recognized three limiting issues in conventional cameras: latency, motion blur, and dynamic range. Latency and dynamic range benefit directly from EBS design. Motion blur leads to smearing of an object in the image, due to camera/object motion during measurement, which makes it difficult to determine the location of an object of interest.

We interpret the benefits of solving the above issues as increasing a platform's agility, improving algorithm precision, and increasing the range of operating environments.

We view computer vision algorithms as often being designed generically to work with a wide range of image/video data inputs, producing generic spatial information about the scene. This general information can add value to many specific tasks. Information includes data such as optical flow, environment maps, object location, and camera position. Tasks are often involved with consumer applications such as self-driving cars or virtual reality and are often operating in human-occupied environments. The data product is consumed by another algorithm as opposed to a human, and this algorithm has expectations on what the data should look like (i.e. there is some concept of an ideal data product.) These traits make it simple to encapsulate many computer vision algorithms in the imaging chain. As such it is simple to measure their performance (i.e. better performance when producing data closer to the ideal product.)

We have observed that computer vision algorithms are usually designed as being task-agnostic, and as such are well suited to performance abstraction. Therefore, measuring performance is relatively simple and straightforward, and performance results and explanations are often simple to understand. However, computer vision algorithm users must specify tasks for their application, which can get complex. Thus, one potential issue with algorithm tests is they are often completed in a laboratory environment with a small subset of potential application scenarios. If a user's tasks are not compatible with a computer vision algorithm's performance interface, this approach can bear significant risk. In this case, additional testing is required by the algorithm user to show performance in a specific application.

In summary, computer vision algorithms can be generalizable and task agnostic, which we view as leading to straightforward performance measurement. However, users must integrate the algorithms into a larger system to complete a specific task, which can lead to complexity for the user in verifying application performance.

2.2 High-speed video reconstruction

By leveraging simultaneous image data collection from EBS and low-speed conventional sensors and fusing these image data streams together one can enable the creation of a high-speed video feed[16]. In this example, performance is evaluated using fidelity metrics including structural similarity and peak signal-to-noise ratio. Other fidelity metrics, such as mean-squared error, are used in similar examples[17]. The goal is to augment the low-speed data with high-speed EBS data, leading to improved performance with conventional computer vision algorithms. Here, we limit discussion to performance evaluation.

Fidelity metrics were used to measure reconstruction performance. While they say little about specific application of the reconstructed video, they can often still be useful for reconstruction performance measurement. Often, algorithms are designed to accept some ideal image as an input. Then, the closer a reconstruction comes to an ideal image, the better an algorithm which expects an ideal image will perform.

The idea behind fidelity metrics is to measure how close a test image is to some ideal image. They are used when an ideal image is required for an application. For example, a broadcast company may need to transmit television images with minimal data bandwidth, but still provide images close to the original to the receiver. Here, data bandwidth is a simple measurement, but it is complex to define what is meant by close to the original, especially when the company does not know ahead of time what specific images are to be transmitted.

A fidelity metric defines what it means for the test image to be close to a reference image. Often, a fidelity metric defines this concept in a way that is correlated to performance. This correlation enables a reconstruction algorithm to compute performance with some accuracy, without knowing the input images or the usage of the output. Here, fidelity metrics are used as a surrogate for a direct performance measurement. This approach is often a good starting point when the application has not been specified. However, when an application has been specified, fidelity metrics usually have lower accuracy compared to now-available application-specific metrics. For example, in similar research,[18] conventional video was reconstructed from only EBS data, and fidelity metrics were used to measure reconstruction performance. Afterwards, the reconstructed images were used as input to other applications, where more specific performance metrics were used.

In summary, performance metrics are often designed to solve a generic problem. The lack of a specific application limits the accuracy and information provided by these metrics, but also allows the simplification of measurement. However, if an application is given, more specific metrics can provide a higher accuracy performance measurement.

2.3 Automatic Target Detection, Tracking, and Recognition

In Automatic Target Detection, Tracking, and Recognition, the goal is to collect target information such as object presence, position, velocity, and type. This information is then used in a higher-complexity application to accomplish tasks. Detection, tracking, and recognition fit within the broader Automatic Target Recognition (ATR) application, and we use the term ATR to represent all of these applications. ATR is a focus of our EBS program, and we direct significant effort towards developing this application.

ATR is distinguishable from computer vision in that it is much more scene dependent, so abstraction is more difficult. For example, ATR is often conducted in a degraded environment, with large temperature ranges, vibrations, and strongly varying weather and lighting conditions, with target detection systems being sensitive to all of these. As such, general performance interfaces, as seen with computer vision, are uncommon in this application.

So far, we have looked at the bandwidth performance of EBS under motion and investigated the bandwidth advantage of EBS, which is a relatively straightforward performance metric[3,4]. We then showed similarity between EBS and a conventional, frame-based imaging system containing a subtract-and-threshold algorithm[2]. This conventional system is well known for automatic moving target detection applications, and the primary difference is that EBS also has an inherent bandwidth advantage. This similarity gives an application in moving target detection, where EBS would likely have strong performance.

We view this analogy as a particularly powerful step in application development, as it provides an application already proven with conventional technology similar to EBS. We then search through this application's specific tasks to find the bandwidth limited tasks, or tasks where EBS will provide an advantage. By using this analogy approach, the search for valuable EBS applications can be constrained, reducing risk and providing a roadmap for future application development.

ATR is a complex application, and we are attempting to improve it with EBS. The first step in our approach was to show similarity to a conventional detection system. This follows the general theme, of simplification through abstraction, using the similarities between conventional and EBS technology. This lets us conclude, if our assertion of similarity is correct, that they have the same/similar applications. This is a top-down approach, where general sets of potentially high-performance tasks are first identified for the EBS. In other cases, a bottom-up approach is used, where applications are developed by demonstrating specific instances of an application. We believe that the bottom-up approach is sufficient for relatively simple applications, but a top-down approach is important with more complex applications. This is because testing for complex applications is expensive, so should only be done when there is high certainty of value-added results.

To conclude, our work so far in ATR has led to defining a top-down approach for evaluating EBS performance. This risk-reduced approach is inspired by systems engineering methods, with more discussion in sections 3 and 4. We believe that the approach is especially useful to developing complex applications and could provide significant value to applied EBS research.

2.4 Application summary

We looked at several different EBS applications, the way they are designed, and limitations in the ways they have been developed. In the first two cases, it could be straightforward to demonstrate application, as the end goal is unspecified, so performance can be measured with general methods. Here, a bottom-up approach is often most effective, as adding additional structure is unnecessary and burdensome. In the last case, the application is more complex, as such demonstrating value becomes complex and expensive. To manage this complexity, we believe that a top-down approach is important, which can reduce risk and costs associated with development.

Next, we will look at a general method that we have developed to realize this approach. We believe that its use can help organize application development and lead to more complex and value-added EBS applications.

3. NEW METHODOLOGY

When developing a complex application, methodology and design structure become important. By complex, we mean that there are many potential tasks, with diverse parameters that application performance is sensitive to. However, it is expensive and often unnecessary to iterate and understand the whole parameter space, and staged engineering methods can be used to search for and select relevant, value-added tasks.

3.1 Systems engineering “V” model

We introduce an engineering method to manage EBS application complexity. This is an implementation of the systems engineering “V” model, where high-level requirements are composed to accomplish an objective. This is followed by specifications which meet the requirements, followed by system design and development which completes some of an application’s tasks. Then, validation steps repeat this order backwards. This involves testing the system, followed by demonstrating that specifications are met, followed by demonstrating that high-level requirements are met. The idea is to go down from a general task objective, to a specific system, and then back up in validation, forming a “V” shape.

An important characteristic of the “V” model is that is outcome-based, in that all steps are based on meeting the objective. As such, all steps can be traced back to the initial objective. As applications become more complex, minor changes in the objective can lead to a significantly different system implementation.

As a system’s development becomes more technical when approaching hardware development, the system and its performance become harder to trace back to high-level, often qualitative, objectives and requirements. Therefore, it is important to verify along the way, whether the developed system and its specifications are still relevant to original tasks and objectives. By verifying, we mean providing evidence of relevance to the original objective. After development, the system must be validated to show that it indeed meets quantitative specifications and requirements. This method is useful, because late-stage development and testing becomes expensive with complex systems and should only be done when there is some certainty of success.

3.2 EBS method

Here, we discuss our proposed method for application development. Note that we will briefly discuss the full method within this paper but will go into further detail in future publications. This method is guided by observations and conclusions in section 2. The idea is that, when developing a complex application, a top-down approach should be used to reduce risk and costs.

This framework is an implementation of the "V" model. The novel part is that it is directed towards more complex EBS application development. The goal here is to show how EBS technology can be analyzed and developed with well-understood engineering methods. This framework would enable methodical development of complex EBS applications.

The goal of the method is to search for, find, and prove value-added EBS applications, with low risk and cost along the way. The approach of this method is to start off with a broad potential application, conducting an increasingly narrow search to show where EBS provides value. Along the way, analysis is conducted with increasing fidelity and specificity, with verification to ensure that the EBS still provides value to the application. This is similar to the "V" model, as at early stages few resources have been expended, so if analysis provides insufficient evidence for, or invalidates an application, it will come without large sunk costs.

We view this as a multi-step process, with testing between each step to demonstrate application value. Often, potential EBS applications currently use conventional, frame-based sensors. If this is the case, relative performance between conventional and EBS technology must be measured to show added value. Here is a list of the steps, and we will go into some detail about each.

1. Initial value proposition (Determine potential value-added tasks)
2. System-level simulation and analysis
3. Higher fidelity, component-level simulation and analysis
4. System design and development

We believe that these steps integrate to form a process that can minimize risk and cost and can lead to robust applications. By integrate, we mean that each step is informed by the step before it, and each step is verified to show that it is relevant to the previous step. In the literature, we have seen instances of steps 1, 3, and one instance of step 4. We have not seen step 2. While several of these steps are individually implemented in the literature, by integrating them together to develop an application, efforts can be focused on the same objective every step of the way. This is opposed to completing steps individually, where application development described in one publication may or may not be relevant to somebody else developing a similar application. This can lead to rework or application invalidation, with additional performance testing relevant to specific task(s) being required.

The initial value proposition consists of research in demonstrating potential EBS value. This can take many forms. In a previous work[4], we used the analogy to conventional technology to demonstrate potential areas where EBS adds value (Note that this does not reveal the full potential of EBS, but only the applications related to the conventional technology). We view this approach as low risk, as it can specify a general of class of tasks, which can be searched and down selected from in future steps. Others have used proof-of-concept methods to demonstrate potential value[19, 20]. Here, researchers discover an application in a bottom-up approach, demonstrating specific instances of an application. We view this as a high-reward, high-risk approach, as it can demonstrate many novel EBS applications which would be expensive or cumbersome to discover with the analogy method. In other words, in many cases analogies are not available for a valuable EBS application, so this is an important method for application discovery. However, proof-of-concepts can have trouble generalizing beyond demonstrated tasks, and demonstrated tasks are often a small subset of potential value-added tasks. Thus, this method may work best in simple applications. A third approach is to derive the EBS application from requirements. This is how we view the computer vision[14, 15] application as emerging. Here, generalized application requirements are mapped to positive EBS traits. We view this as a low-risk method. However, in addition to requiring expertise to develop the correct, generalized requirements, the application must also abstract well. It may be useful to use more than one approach, such as proof-of-concept inspiring analogy, or vice versa. This step determines potential value-added tasks and scenarios, which inform the work completed in the next step.

System-level analysis involves an abstraction of EBS performance across relevant tasks. This step refines the initial value proposition, while reducing risk and cost through abstraction of tasks and task performance. This abstraction involves converting functionality from complex EBS behavior into an easily understood form. For example, in the next section, we abstract the EBS as being a conventional camera, plus a bandwidth advantage, and apply surrogate performance metrics to an ATR task. However, when the application is complex, the analysis loses accuracy. If done in an incremental manner, as in this framework, we believe the loss of accuracy can be reasonable and the outcome can inform later steps. This step will be discussed in detail in the next subsection.

Component-level analysis involves constructing specific simulated scenarios and measuring simulated EBS performance in them. The goal is to select, with high fidelity, tasks from step 2 which demonstrate value. By informing this step through step 2, there can be more certainty that some subset of the potential value-added tasks will still be valid. This informs the system development step and allows hardware to be built specifically for tasks with the highest potential.

System design and development involves designing and constructing a hardware prototype which can complete tasks in an application. The goal is to construct a system, which has value added performance in an application's tasks.

The goal of verification is to ensure and prove that the developed system can accomplish tasks specified in a previous step. This ensures traceability, such that the developed EBS system is still relevant to the original application.

In summary, we described a process for developing EBS applications. This is an implementation of standard engineering design methods. While many examples of individual steps can be seen in the literature, they are often uncoordinated with respect to a higher application. In many cases, this is not necessary, as the application allows encapsulation of performance without describing specific tasks. However, moving forward we anticipate much more work in developing complex applications. Here, we see value in this process, as it helps organize research and manage the complexity.

3.3 System-level analysis

System-level analysis attempts to refine potential value-added tasks suggested by the initial value proposition. The goal is to select the tasks from the initial set that could benefit from EBS. The idea here is that performance can be described, with some accuracy, with a simple, abstract, mathematical model. Additionally, scenarios should also be described with an abstract, general mathematical model, with performance being a function of the scenario. Finally, the scenario and performance models have parameters which should be processed to determine performance from the initial set of tasks. This step should be informed by the initial value proposition, refining the set of tasks provided by that step.

We view the outcome for each task to be one of three cases. First, both EBS and conventional technology can have insufficient performance for an application's tasks. Here, the modeled EBS is not good enough, but future models may have the potential to sufficiently perform. Second, EBS can have sufficient performance, but so does conventional technology. Here, EBS can successfully perform the application's tasks, but this does not add value, as conventional technology is already good enough. Third, EBS can have sufficient performance where conventional technology does not. Here, EBS adds value by improving the application in ways that conventional technology cannot.

The performance model describes performance as a function of the scenario. It takes parameters describing the EBS and a comparison conventional camera, if applicable. This model may need to measure conventional technology performance, as the two would need to be compared in the same way to show relative EBS performance. Note that the accuracy of this model does not need to be great, but only sufficient for partitioning the set of tasks into possibly value-added and non-value-added sets. Assumptions for describing this model and how the two sensors are compared should be explicitly stated and discussed.

The scenario model mathematically describes the scene and anything happening in the scene. This should be guided by the initial value proposition, with tested scenarios based on potential value-added tasks. In other words, the set of model parameters form a domain which should represent this set of tasks. The performance model should then be able to operate throughout this parameter space to compute performance.

This step adds value to the application development process in several ways. First, it refines the value proposition, providing clearer evidence of EBS value to the application. This can lead to more focused, informed work in later stages of development, as opposed to when completing component-level analysis and development first. Second, it reduces cost, as determining if EBS benefits some tasks early on can be simpler than doing so at later stages. Third, it may inform other applications, as general approaches used in this analysis may transfer well to other applications.

In summary, we described the system-level analysis step of our proposed method. First, we described the expected outcomes of the step, as well as the necessary components. We then described the value added through completing this step. While this approach is abstract, we will be providing an example of its usage in the next section, applied to ATR.

4. APPLICATION EXAMPLE

4.1 Problem description

The goal is to detect a target, using an electro-optic imager (e.g camera in a visible or infrared band) in a low-dimensionality parameter space. To simplify the initial analysis, this problem is assumed to have only one-dimensional variations in geometry, as well as variation in background clutter. The target will be located at a variable distance from the target. The electro-optic imaging platform must operate at a fixed equivalent frame rate, which is how temporal resolution is specified. The target needs to be detected with some probability of success, with a constant false alarm rate.

4.2 System description

The system will consist of the imaging platform at some distance from the target. The target will subtend some angle when seen from the electro-optic imager's perspective, with this angle changing with distance.

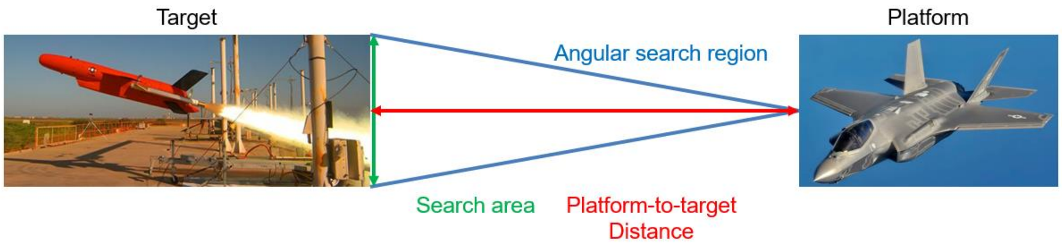


Figure 1: A cartoon showing important system parameters. The target (Target drone on left) is identified as being within a search area. The EO imager platform, at some distance, must then search this area and find the target.

The system has geometrical degrees of freedom. In other words, we are viewing it as having varying target distance, as well as some pre-defined search area, within which the electro-optic imager must find a target. This search area is assumed to be given, although more complex systems could be defined which define this area based on other geometric parameters. This search area also subtends some angle, which is also a function of platform distance from the target.

The electro-optic imager is assumed to have an ideal lens and performance is assumed to be data bandwidth limited (i.e. limited pixels output per second, no aberration, noise, diffraction, or other limitations) at the detector. The electro-optic is the abstract model representing the EBS and a conventional digital camera. The model electro-optic has ideal optical zoom capabilities and can reconfigure such that the angular search area completely fills the focal plane. This model assumes that all noise sources are insignificant, and system performance does not depend on noise.

One important assumption in this system is that the EBS collects equivalent information relevant to a conventional camera with the same full and instantaneous fields-of-view. This is an optimistic assumption and we expect to demonstrate significant differences in future research.

4.3 Performance metrics

It is important to define performance for the system, as well as how to translate EBS advantages into improved performance. Often, for detection tasks, performance is measured in terms of probability of successful detection and target localization, with a constant false alarm rate. We will be following this approach.

4.3.1 Johnson Criteria

In measuring imaging system performance with probability of detection, a common choice is the Johnson Criteria and similar metrics[21, 22]. These are surrogate metrics which predict imaging system performance without directly measuring probability of detection. These metrics are based around psychophysical studies and provide a mapping of target resolution as seen from the detector, to probability of detection. Here, probability of detection means the probability of target detection and localization, often with an implicit false alarm rate. This value is often given as the minimum number of line pairs, or equivalently pixels-on-target, required for a 50% chance of success with an implicit false alarm rate.

To measure this pixels-on-target value, the electro-optic imager's field-of-view requirement is translated, with additional geometry information, into an instantaneous field-of-view, which gives the angle subtended by one pixel in the electro-optic. Given the distance from electro-optic to target, this angle converts to a linear distance occupied by one pixel. This linear distance, in meters, is then divided by the size of the target (the largest dimension) in units of target length. The result, pixels-on-target, is in units of pixels per target length.

Variants of the Johnson Criteria[23,24] investigate the concept of using a clutter level (high, medium, low) as a parameter for measuring probability of detection. Additionally, one work[24] provides a full mapping (as opposed to a 50% success pixels-on-target value) of detection performance to pixels-on-target, with an explicit false alarm rate of 10% (i.e. 10% chance of detecting a target when no target is present in the scene). Figure 2 shows a reconstructed plot of data points.

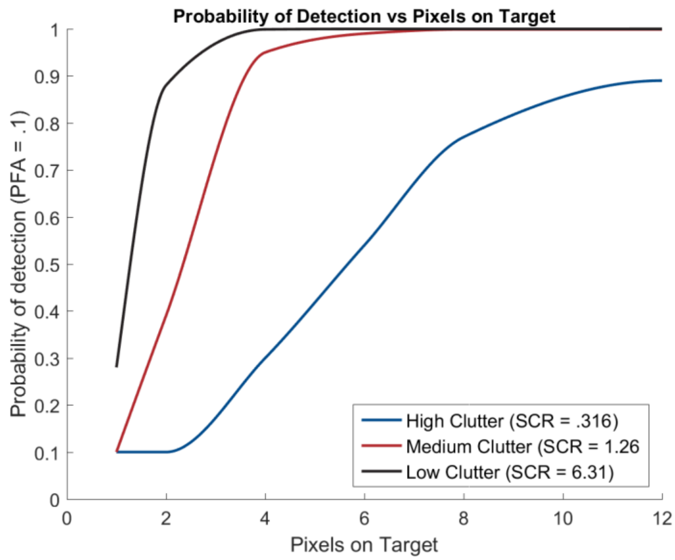


Figure 2: The mapping used between pixels-on-target and probability of detection, given explicit false alarm rate. This was created by interpolating data points from the aforementioned publication[24].

We believe that we can use this mapping to provide a system-level description of electro-optic imager performance. As the scenario provides parameters through which probability of detection can be computed, we can now describe task performance.

4.3.2 EBS improved performance

We abstract the EBS as a conventional camera plus a bandwidth advantage. By bandwidth advantage, we mean that we abstract the EBS as reading out the same relevant information as the conventional camera in a period of time, but the EBS requires less data to do so. For example, a 1,000-pixel focal plane has 100 relevant pixels describing the scene, and all data outputs with a repeating period. If the conventional camera outputs all 1,000 pixels in a time period (defined with the equivalent frame rate) and the EBS outputs only the 100 relevant pixels in the same time period, then the EBS would have a 10x bandwidth advantage.

The idea is that this advantage translates into improved performance. Bandwidth, B, in units of pixels per second, can be viewed as a composite performance metric, as the product of three measures. These include spatial resolution, S (In one dimension, pixels per radian), field-of-view, F (In one dimension, radians per field-of-view equivalent), and temporal resolution, T (equivalent frame rate, or field-of-view equivalents per second). This perspective shows a trade space between these parameters. In other words, bandwidth is often a limiting trait of an imaging system, as there is a finite data throughput of a sensor. Note that this is assuming that performance is limited by detector data bandwidth. Below, Equation 1 concisely describes the trade off and Figure 3 gives a graphical example of how the three parameters interact, given constrained bandwidth.

$$B = FTS \tag{1}$$

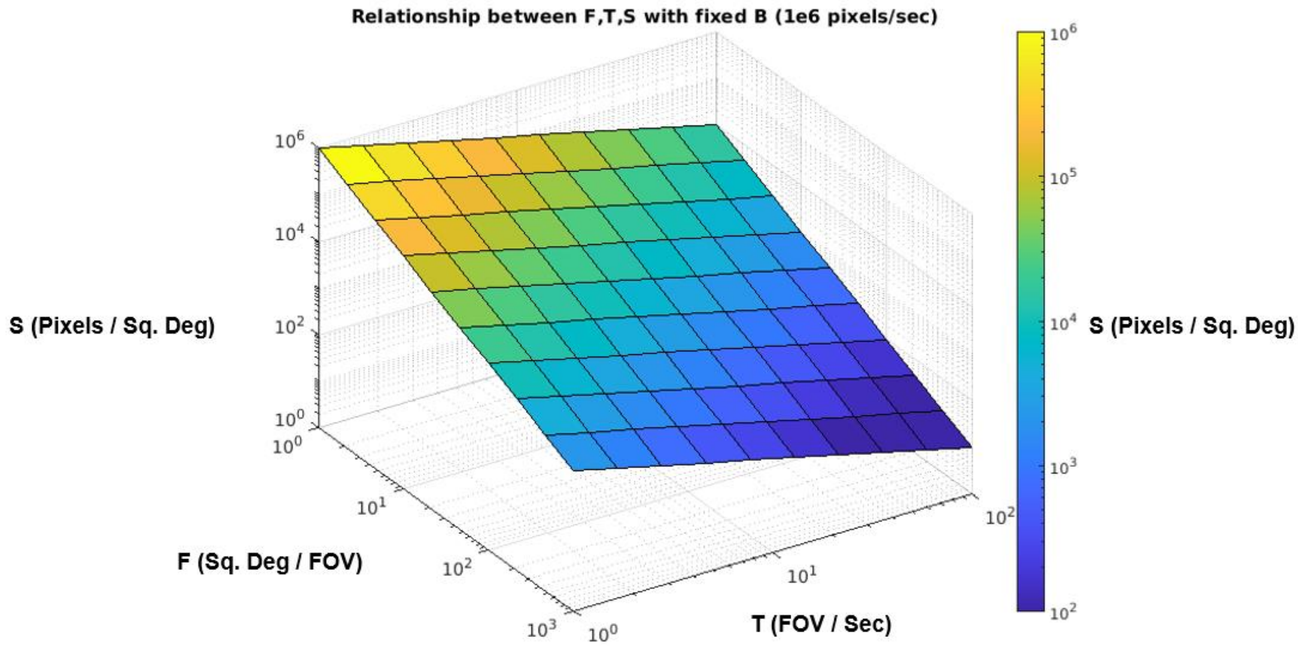


Figure 3: Trade space showing an example of the three system parameters with constant bandwidth. Given this bandwidth constraint, when the product of T and F is small, S can be large (High value on color bar). When the product is large, S is constrained by a much smaller value (Low value on color bar).

The EBS abstraction enables application of this trade space to both sensors, as EBS does not operate with frames. This abstraction might be viewed as representative of EBS behavior in some cases. Specifically, it assumes that EBS outputs data at a constant rate and that events are binned into frames with a constant timestep, with a constant number of events per time step. This may or may not be reasonable, as scenes are often changing, which changes the data rate. However, ATR is often conducted with natural scenes that have statistically similar appearance over time.

The performance advantage of improved bandwidth is that the trade space is expanded, when unaffected by limitations described earlier, including aberration, diffraction, and noise. Temporal resolution is often specified as a parameter through previous performance experience. In other words, some threshold equivalent frame rate is required for good performance. Field-of-view is specified by the scene geometry and spatial resolution is unspecified but is limited by the other two parameters.

The increase in B from the EBS, translates directly into an increase in S. When combined with scene geometry, S can be converted to pixels-on-target. This leads, through the Johnson criteria, to an increase in probability of detection. This is the performance comparison that we seek, as it shows how EBS improves performance. Figure 4 graphically illustrates how, when field-of-view and temporal resolution are fixed, increased B translates to increased S.

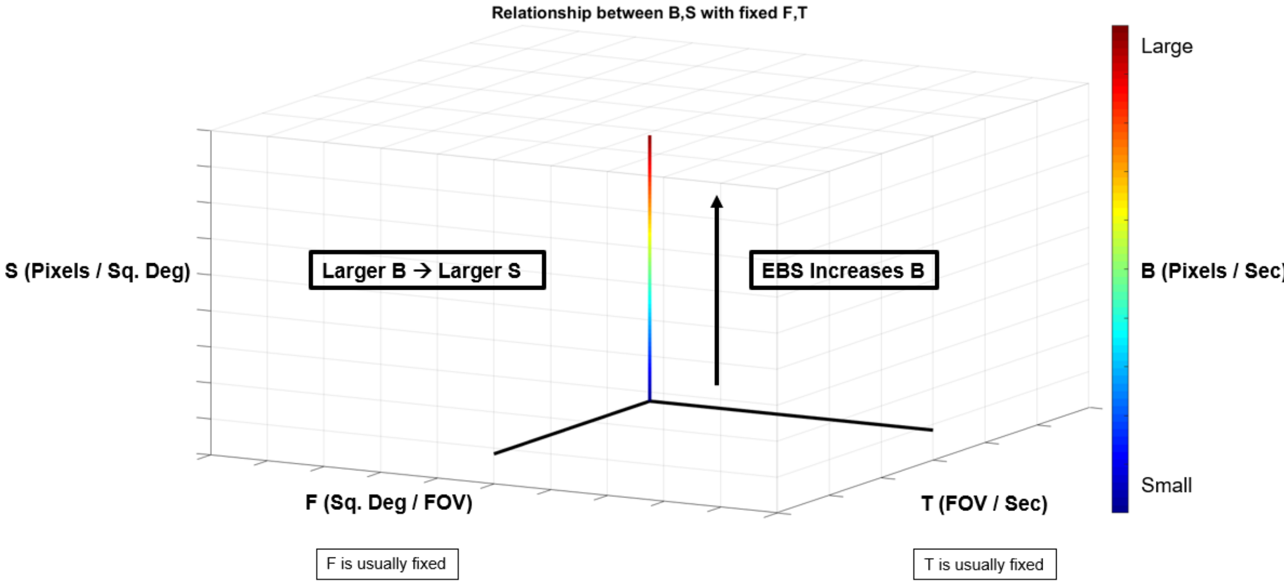


Figure 4: A plot showing traversal of the trade space. The improved EBS bandwidth (B) is used to increase spatial resolution (S) . Increases in B and S correspond to higher values on the color bar. With everything else equal (Fixed T and F), this improves performance by the Johnson Criteria.

As stated earlier, EBS is modeled as a conventional camera with superior bandwidth performance. Using the earlier discussion, this bandwidth increase leads to increased spatial resolution. Through geometry and the Johnson Criteria, this leads to superior performance. However, as this is abstract, the process of increasing spatial resolution is unspecified. While this is currently limited by EBS focal plane array sizes, recent prototypes and future, commercially available devices are approaching and are expected to surpass a megapixel[25].

4.3.3 Limiting assumptions

There are many assumptions in using the above mapping which should be discussed, as this analysis loses accuracy when these assumptions are not reasonable. Several of the more significant assumptions are discussed here.

We assume that EBS collects the same relevant information as conventional technology. This assumption dismisses differences such as EBS time stamp data, higher dynamic range, and change detection functionality, and assumes that their effect on performance can be modeled with the bandwidth advantage. The assumption also dismisses negative traits such as high noise and low sensitivity.

Johnson Criteria-like metrics assume a human observer. If, in lower-level analysis, a human-like detection algorithm is not used, there may be significant differences in performance versus this model.

We assume that the abstracted target and scene are well-represented by the data used to derive Figure 2. This data assumed natural scene statistics with military targets, which matches well with the ATR application. Note that phenomena such as lighting and weather would be accounted for by changes in the signal-to-clutter measure.

We assume that the detection system's performance is limited by focal plane size. This dismisses other potentially limiting factors such as optics, noise, or algorithm performance.

These assumptions limit the representativeness of the analysis results. However, for many system-level analyses, these limitations are reasonable. As discussed in Section 2, it can be useful to assume generalities in value-added tasks in order to simplify analysis. As discussed in Section 3, this approach fits with the spirit of high-level analysis, which is to generalize, enabling low-cost analysis that can refine potential tasks and inform more accurate low-level analysis.

This analysis uses correlative, indirect methods of measuring performance, instead of constructing an imaging system model. This approach leverages decades of imaging system experience and research, saving significant resources and effort, but trading off with a loss in accuracy. This is opposed to direct analysis of the EBS system, which while more accurate, requires significantly more detail than the indirect, high-level approach. While we view the direct analysis as necessary, we believe that conducting the system-level analysis, as a first step for informing and designing the direct analysis, is useful.

Next, we provide a specific example analysis to show how results might be computed and interpreted.

4.4 Example analysis parameters

Table 1: Specific parameters used in simulation.

Parameter	Value
Sensor Pixels (1D)	640
Target Search Area	2,500 Meters
Target Size (1D)	10 Meters
Conventional Camera Frame Rate	30 FPS
Conventional Camera Bandwidth	100,000,000 Pixels/Second
Platform-to-Target Distance	1000-30,000 Meters
EBS Bandwidth Advantage	10x or 40x
Signal-To-Clutter Level	0.316 (Low)-6.3 (High)

We investigate three clutter levels, high medium and low, similar to that specified in the probability of detection table[24]. These values represent signal-to-clutter ratios. The average irradiance of target pixels divided by the average irradiance from background pixels, across the whole field-of-view, was used to compute these ratios.

4.5 Analysis results

We computed results for the application's scenario variations, given the parameters above. Figure 5 shows the relationship of pixels-on-target to distance in this geometry. Figure 6 gives probability of detection performance under the different clutter levels.

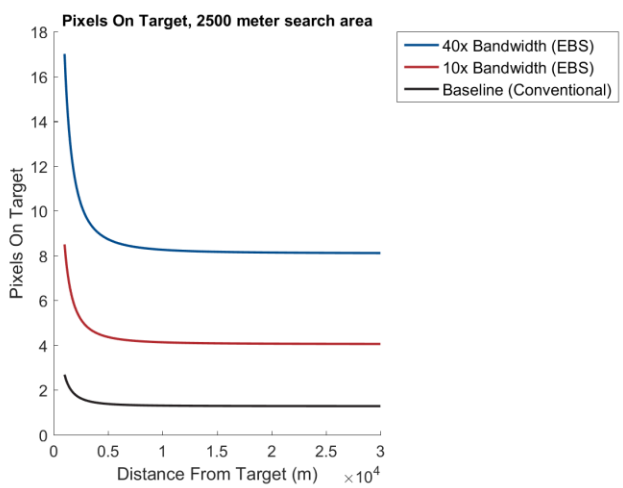
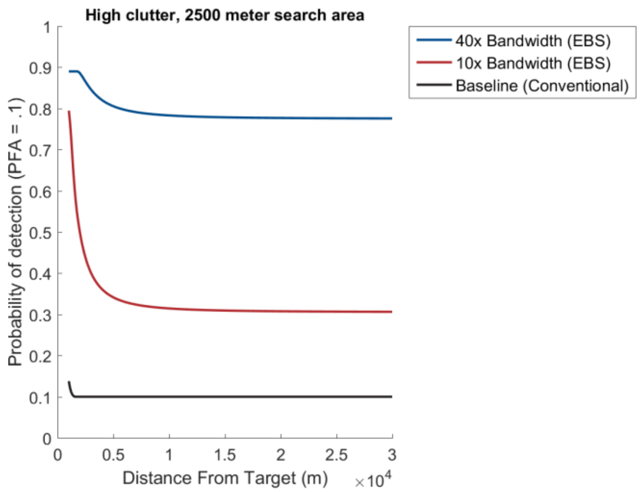
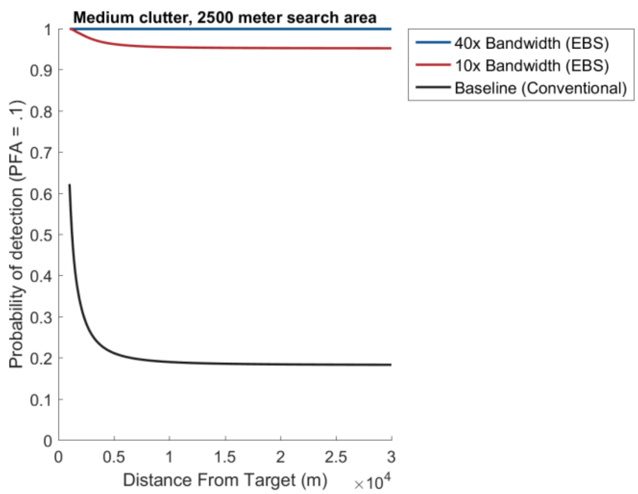


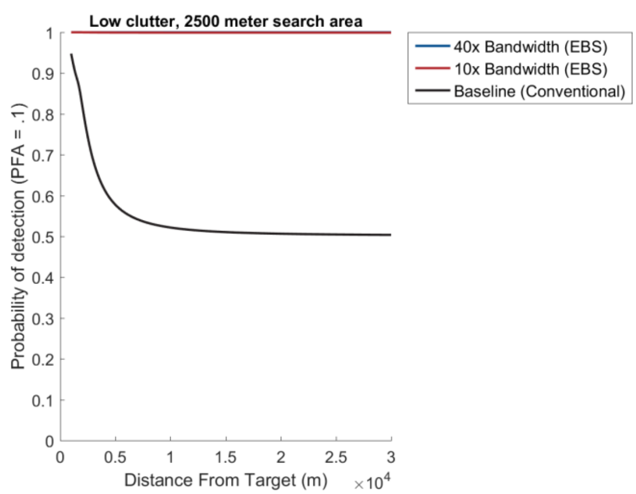
Figure 5: A plot of pixels-on-target versus distance, using parameters from Table 1.



(a)



(b)



(c)

Figure 6: Probability of detection and localization versus distance in high (a), medium (b), and low (c) clutter.

In Figure 5, as bandwidth improved (abstracted EBS advantage), pixels-on-target increased. Pixels-on-target are relatively constant outside of close ranges. At long ranges, a small angle is formed when imaging the field-of-view. There, a small angle approximation leads to a nearly linear increasing field-of-view with decreasing distance. This linearity cancels out with the linear increase of target angular size, leading to constant pixels-on-target. At a closer positions, where the approximation fails, pixels-on-target increases. Here, the target size still increases approximately linearly on the focal plane, while the field-of-view now increases at a sublinear rate.

In Figure 6, we show sensor models, with high, medium, and low clutter performance for each. Two represent abstracted EBS performance, and one represents conventional technology. The EBS plots represent a bandwidth improvement of 10x and 40x. In other words, we assume that EBS is equivalent to conventional technology, except it has a 10x or 40x bandwidth performance increase.

Based on requirements from some more complex application, one might view high performance as having probability of detection and localization above 0.9, marginal performance as above 0.5, and insufficient performance as below 0.5. In Figure 6, regions can be seen where the conventional technology has insufficient performance, but EBS has marginal or high performance due to the bandwidth advantage. These regions correspond to where EBS (given the bandwidth improvement) provides value. For example, in medium clutter at long ranges, the conventional technology has insufficient performance, but both EBS models reach high performance. There are also regions where both EBS and conventional technology have insufficient performance. These are scenarios where EBS could contribute if it had more performance. For example, in high clutter at long ranges, 10x bandwidth improvement only reaches marginal performance, but 40x approaches high performance. There are also regions where conventional technology has sufficient performance. These are regions where EBS does not provide value. For example, in low clutter at close ranges, conventional technology is sufficient.

Under high clutter, the example conventional imager performed poorly. The 10x bandwidth model performed better, but performance was still insufficient in the absolute sense. However, 40x bandwidth improvement significantly increased probability of detection, approaching high performance. Under medium clutter, the example conventional imager performed poorly when distant from the target. The 10x bandwidth performed much better, reaching a sufficient performance level. The 40x bandwidth improvement had marginally better performance to the 10x improvement. In low clutter, the conventional imager starts to perform marginally, but the bandwidth-improved imagers have already saturated in performance.

As the clutter level increases, the range of value-added EBS scenarios increases. This suggests that EBS may provide significant value in cluttered environments. Although the input scenarios were simple, these results could be used to illustrate the target detection performance potential of EBS.

The goal of this example is to implement the method described in Section 3. We presented an example application and provided details on its description and analysis. We then gave a specific implementation of the task, as seen in the parameter table. Finally, we conducted simulations based on these parameters, and showed how EBS might add value to the example application. This example is how we imagine implementation of the high-level analysis step, which takes a potential set of value-added tasks and searches and selects from them to create a more refined set of value-added tasks. Additionally, the concepts used in this example could be components in modeling more complex EBS applications.

5. CONCLUSION

We looked at many aspects of EBS technology, first starting off with discussion of the device. Then, we discussed several applications. This involved the application, how they were measuring performance, and how this relates to building a more complex application. From here, we concluded that we need new methodology to handle high complexity in EBS application development. We presented this methodology in the next section, focusing on a specific step for system-level analysis. We then presented an example implementation of this step, where we used system-level models and surrogate performance metrics to predict task performance for an automatic target recognition application. We believe that this publication is a new direction for EBS research and has the potential to facilitate complex EBS application development.

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