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Information-based Intelligent Unmanned Ground Vehicle Navigation

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***Abstract*— Sensor-centric navigation of Unmanned Ground Vehicles (UGVs) operating in rugged and expansive terrains requires the competency to evaluate the utility of sensor information such that it results in intelligent behavior of the vehicles. In this paper, we propose an entropic information metric for the above purpose where entropy is used to quantify the probabilistic uncertainty in sensor measurements. We present results using data obtained from field trials on an unmanned vehicle to substantiate the utility of the proposed metric. We also show how low and high level tasks can be predicated upon this metric in potential application areas related to autonomous vehicle navigation.**

I. Introduction

The quantification of information contained in sensor measurements and its efficient utilization for generating intelligent behavior of Unmanned Ground Vehicles (UGVs) operating in unstructured, expansive and harsh rugged terrains is the main theme of this paper. In the context of this paper, *unstructured* implies a physical environment that does not have much regular structure or layout. An *expansive* environment is one which is much larger than the range of the sensors available on the vehicle. *Harshness* refers to the uneven undulatory terrain of the operating environment.

Various researchers have employed entropy as a measure of information. Roy *et al.* generate a map of the environment that contains the information content of each position in the environment. The information content is computed off-line from an *a priori map* [15]. Beckerman [3] presents a Bayes-maximum entropy formalism for fusing ultrasound and visual data acquired by a mobile robot to construct a map for navigation. In [4], a composite utility metric based on the ideas of entropy has been developed for the dual objective of mapping and localization for an indoor multiple robot team. Musto and Saridis have employed entropy for reliability analysis of intelligent machines [12]. Entropy has found its use in encoding prior knowledge about the discriminability of objects as a function of viewing position [2] and in the so-called optimal sensor placement techniques [18]. In recent years, entropy has also been extensively utilized in decentralized and distributed data fusion systems [11], [13].

Even though entropy has been used in a wide array of sensor fusion applications, its use has been very limited in the image interpretation, pattern recognition and matching areas with respect to outdoor robotic vehicle navigation tasks. This paper borrows ideas from information theory towards the development of a scheme for images obtained from typical sensors that are utilized in such domains. We propose an entropic metric for the evaluation of information of sensed images and show that this metric serves as a strong intuitive measure for evaluating and ultimately utilizing sensor measurements for robotic navigation tasks.

The paper is organized as follows: Section II introduces the concept of entropy. This is directly followed by the methodology by which the entropic information of images obtained from various sensing modalities can be obtained. Section III shows how the proposed metric can be employed in the information evaluation of images for two sets of mobility sensors. Section IV shows the utility of the information evaluation of sensory perception for UGVs in three different areas of robotic navigation. Section V provides conclusions and avenues for further research.

II. Information Evaluation of Sensed Images

A. The Concept of Entropy

Entropy is a quantitative measure of the uncertainty associated with a probability density function. Since its introduction in classical thermodynamics, the entropy function has been widely applied in communications and systems theory. The entropy of a probability distribution $p(\mathbf{x})$ defined on a random variable $\mathbf{x}$ is defined as the expected value of the negative of the log-likelihood[1] [14] and is given by:

$$h(\mathbf{x}) \quad \triangleq \quad \mathrm{E}\{-\ell n p(\mathbf{x})\}$$

[1]In this paper, the log is taken to mean the natural logarithm to the base *e*. When natural logarithm to the base *e* is used, the units for entropy is *nats*. In telecommunications, it is common to take all logarithms to base 2 and entropy is consequently measured in *bits*.

where E denotes the mathematical expectation operator. For discrete random variables

$$h(\mathbf{x}) \quad = \quad -\sum_{x \in \mathscr{X}} p(\mathbf{x}) \ell n p(\mathbf{x}) \qquad (1)$$

The entropy $h(\cdot)$ is a measure of the average uncertainty of a random variable and thus represents the *compactness* of the probability distribution, $p(\mathbf{x})$. Subsequently, it is a measure of the *informativeness* of the distribution and consequently the entropy is minimum when information is maximum.

B. Computing Entropic Information of Sensor Images

Equation (1) can be rewritten as:

$$h(p_1, p_2, \ldots, p_n) \quad = \quad -\sum_{k=1}^{n} p_k \ell n p_k \qquad (2)$$

where p_k is the probability associated with the k^{th} event.

Entropy can be used to measure the information gained from the selection of a specific event among an ensemble of events. It can be seen from Equation (2) that $h(p_1, p_2, \ldots, p_n)$ is a maximum when $p_k = \frac{1}{n};\ k = 1, \ldots, n$ and thus uniform probability distribution yields the maximum entropy (minimum information).

The gray-level histogram of the sensed images are used to define a probability distribution such that:

$$p_i \quad = \frac{N_{p_i}}{N}; \quad i = 1, \ldots, N_g \qquad (3)$$

where N_{p_i} is the number if pixels in the image with gray-level i, N is the total number of pixels in the image, and N_g is the number of gray-levels, respectively. Using Equation (3) in Equation (2) yields the entropic information. As noted in Section II-A, the entropy is maximum for an image in which all p_i are same. Thus, the less uniform the histogram, the lower the entropy and higher the information content of the image.

III. EXPERIMENTAL SETUP AND RESULTS

The primary goal of the U.S. Army's Demo III e**X**perimental **U**nmanned **V**ehicle (XUV) program [17] is to develop and demonstrate technology required to develop survivable mobile robots capable of autonomous operation over rugged terrain as part of a mixed military force, containing both manned and unmanned vehicles. The XUV shown in Figure 1 is a hydrostatic diesel, 4 wheel drive, 4 wheel steer vehicle utilizing the NIST developed **R**eal-Time **C**ontrol **S**ystem (RCS) [1] using Neutral Message Language (NML) communications for autonomous navigation in unstructured and off-road driving conditions.

Fig. 1. The Demo III eXperimental Unmanned Vehicle can drive autonomously at speeds of up to 60 km/h on-road, 35 km/h off-road in daylight, and 15 km/h off-road at night or under inclement weather conditions. The Camera is mounted above the LADAR shown in white.

The sensor suite of the XUV consists of a pair of cameras for stereo vision, a Schwartz[2] Electro-Optics LADAR (**LA**ser **D**etection **A**nd **R**anging), a stereo pair of **F**orward **L**ooking **I**nfra-**R**ed (FLIR) cameras, a stereo pair of monochrome cameras, **G**lobal **P**ositioning **S**ystem (GPS), **I**nertial **N**avigation **S**ystem (INS), a force bumper sensor and actuators for steering, braking and transmission [6]. An integrated Kalman filter navigation system fuses measurements from odometry, inertial and differential GPS sensors for position estimation.

The primary sensors we are interested in for the purposes of this paper are the camera and the scanning laser range finder mounted on a pan-tilt platform. The camera produces images at up to 30 Hz. The LADAR produces a 32 row $\times$ 180 column range image with a field of view of $20^\circ \times\ 80^\circ$ at 20 Hz. Field data was acquired as the vehicle traversed rugged terrain on an experimental site at Fort IndianTown Gap, PA.

Figure 2 shows the Camera and LADAR images and their gray-level histograms, respectively. To construct the histogram of the intensity images, the default value for the number of bins has been selected to be 256. The horizontal axes of the histograms in Figure 2 represent the gray-level values and the vertical axes represent the number of times the corresponding gray-level occurred in the image. Peaks in the histogram are indicative of particular structures (features) that are present in the scene from which the image was acquired. Once the histograms are constructed, it is straightforward to obtain the information content of Camera and LADAR images by using Equations (3) and (2).

[2]Commercial equipment and materials are identified in this paper in order to adequately specify certain procedures. Such identification does not imply recommendation or endorsement by the National Institute of Standards and Technology, nor does it imply that the materials or equipment identified are necessarily the best available for the purpose.

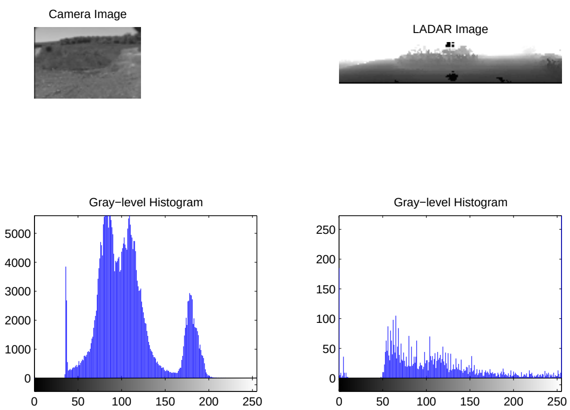


Fig. 2. Sensed Camera and LADAR Images and their gray-level histograms. In the histograms, the horizontal scale is brightness and the vertical scale is the number of pixels in the image with that brightness value. In the LADAR image, dark pixels are close to the sensor and light pixels are farther away.

Figure 3(a) (shown in the next page) depicts three scenes as the vehicle traversed the terrain. The first Camera image shows the scene from the farthest distance of all the three images, and the third image is the closest. As witnessed by the values marked in the histogram plots, the entropy of the third image exceeds that of the other two and can be interpreted as follows: As the vehicle moves closer to the scene, the features of the scene are viewed with better clarity as a result of reduction in the number of visible features. Accordingly, the histogram of the third image is more uniform than the other two resulting in a higher entropy value. This type of information evaluation is analogous to the *scale space* concept. In scale space schemes, an image is analyzed at varying levels of detail for various purposes including feature extraction. At a finer scale level, several features exist than at a coarser scale level where fewer features persist. Accordingly feature identification is done at the coarsest scale, and the feature is localized at the finest scale [8]. These ideas have their use in map registration (Section IV-A).

In Figure 3(b), two sets of similar scenes as viewed by both the Camera and LADAR are shown. The left column depicts the Camera images and their histograms while the right column shows the same for the LADAR images. The entropy values for these images are obtained as before and are marked in the histogram plots. For the particular scene under consideration, it can be clearly seen that the LADAR images contain more information than their Camera counterparts. Even though for the data sets considered in this paper, the LADAR images have been found to contain more information, it is not always the case. In fact, information evaluation of other sets of data have shown that Camera images contain more information and thus it should be emphasized that the underlying information is scene-specific.

In the following paragraphs, we show how the proposed metric can be used in various tasks related to unmanned ground vehicle navigation.

IV. Potential Application Areas

Before we proceed further, we describe the RCS [1] to better understand the navigation tasks within which the proposed metric has its utility. The Demo III XUV was designed in accordance with the RCS reference model architecture. It consists of a multi-layered multi-resolutional hierarchy of computational nodes, each containing elements of sensory processing, world modeling, value judgment, behavior generation (path planning) and a knowledge database as shown in Figure 4. These nodes receive goals, priorities, and plans from superiors and produce the same for subordinates.

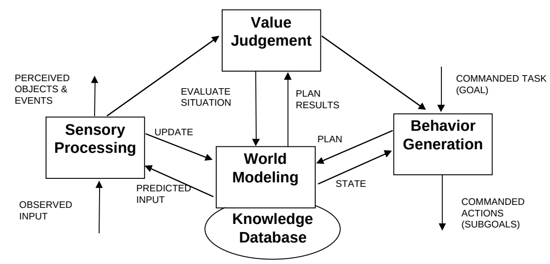
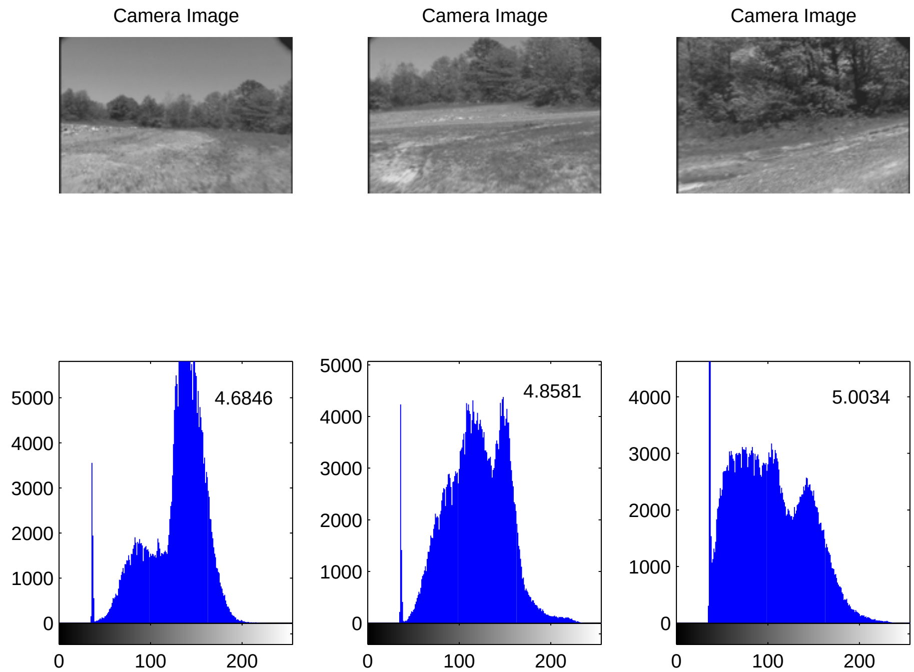


Fig. 4. Internal Structure of an RCS Node. The functional elements within a RCS node are behavior generation (task decomposition and control), sensory processing (filtering, detection, recognition, grouping), world modeling (store and retrieve knowledge and predict future states), and value judgment (compute cost, benefit, importance, and uncertainty). These are supported by a knowledge database, and a communication system that interconnects the functional models and the knowledge database. This collection of modules and their interconnections make up a generic node in the architecture. Each module in the node may have an operator interface.

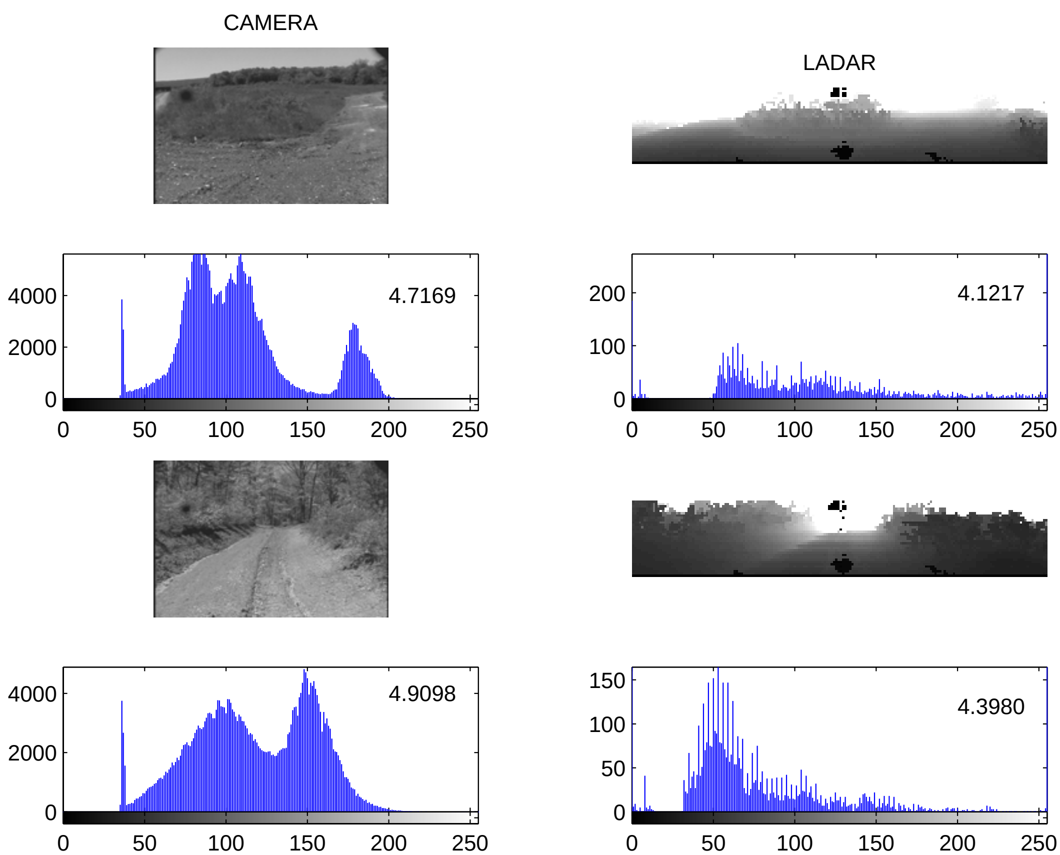
For Demo III, the RCS architecture consists of five levels: Section Level, Vehicle Level, Subsystem Level, Primitive Level, and Servo Level. The Section Level receives a general plan generated by a human. This plan contains general commands and a plan based on *a priori* information from various sources such as digital maps. At the Vehicle Level, the vehicle refines the commands from the Section Level by developing a plan based on its world model that contains information from digital maps and low-resolution information from on-board sensors. At the Subsystem Level, path planning for avoiding obstacles in the path is performed. The Primitive Level controls the steering, acceleration and braking of the vehicle, and the Servo Level controls the actuators for each of the subsystems.

A. Map Registration

Recent developments in miniaturization and increased computer processing capabilities have led to significant



(a)



(b)

Fig. 3. (a) depicts three Camera images and (b) depicts two sets of similar scenes as seen by Camera and LADAR. The corresponding entropy values are marked in the histogram plots. In the histograms, the horizontal scale is brightness and the vertical scale is the number of pixels in the image with that brightness value. In the LADAR images, dark pixels are close to the sensor and light pixels are farther away. See text for further details.

improvements in LADAR devices which are now small enough to operate on aircraft and in ground vehicles. In the near future, such systems will allow military aircraft to identify enemy ground vehicles accurately in battle zones and permit spacecraft and robotic vehicles to navigate safely through unfamiliar terrain. Motivated by these considerations, we are developing robust LADAR registration algorithms for unmanned vehicles [9]. We also envisage the results from the registration to be useful for terrain mapping and in scenarios where GPS is unreliable or unavailable within required accuracy bounds.

Specifically, we are interested in registering LADAR scans to *a priori* maps for use in UGVs. In RCS, the Vehicle Level world model includes feature and elevation data from *a priori* digital terrain maps such as information about roads, bridges, streams, woods, and buildings. This information needs to be registered and merged with data from the Autonomous Mobility level maps that are generated by sensors. By image segmentation and thresholding[3], the objects of interest (features) can be extracted from the sensed images. The information metric can facilitate in this process of reducing images to information (see Figure 3(a)) so that the sensed images can be reliably registered to *a priori* maps. This is an area that is being actively investigated.

B. UGV Localization and Mapping

The Kalman filter (and its variants thereof) has been extensively employed for autonomous mobile robot localization and mapping including the eXperimental Unmanned Vehicle. In such applications, the selection of stable features using sensor measurements is an important issue. To select features from a given vehicle location in a reliable and robust manner, in addition to the uncertainty of the measurements either due to the physics of the sensors, or as a byproduct of the environment, the uncertainty associated with the vehicle location itself has to be taken into account. The entropic metric can be easily applied for this purpose.

For use with Kalman filters that assume Gaussian distributions to model sensor uncertainties, a mathematical expression for entropy can be derived. Consider an n-dimensional state vector $\mathbf{x}_k$ conditioned on a stacked observation vector denoted by $\mathbf{Z}_k \triangleq (z_1, z_2, \ldots, z_k)$ where $z_1, z_2, \ldots, z_k$ are individual sensor measurements. Using Bayesian statistics, the *posterior entropy* can be derived to be [5]:

$$\begin{aligned} h_{k|k} &\triangleq h\left(p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right)\right) \\ &= \mathrm{E}\left\{-\ell n\ p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right)\right\} \\ &= 0.5\ \ell n\left((2\pi e)^n \left|\mathbf{P}_{k|k}\right|\right) \end{aligned}$$

where $\mathbf{P}$ is the covariance matrix that captures the vehicle pose uncertainty.

The *posterior* and *prior* information metrics can then be defined as:

$$\begin{aligned} im_{k|k} &\triangleq -h\left(p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right)\right) \\ &= -0.5\ \ell n\left((2\pi e)^n \left|\mathbf{P}_{k|k}\right|\right) \\ im_{k|k-1} &\triangleq -0.5\ \ell n\left((2\pi e)^n \left|\mathbf{P}_{k|k-1}\right|\right) \end{aligned}$$

The resultant information contribution, ic, from measurements, is thus given by the relation:

$$ic_{k|k} \triangleq im_{k|k} - im_{k|k-1} \tag{4}$$

Using Equation (4), it is straightforward to include the features' measurement that provides the maximum information for localization and mapping. The metric evaluates information content of measurements thereby facilitating the acceptance or rejection of features. The metric has been shown to be an optimal way of efficiently utilizing measurements by implicitly incorporating the features' utility towards reducing localization error and in the selection of the sensing modality/scheme that provides maximum information [7]. Since the information metric provides a scalar value, it is a suitable representation for decision making.

C. Utility-driven Behavior Generation

The entropic information metric can be readily integrated into the behavior generation module of RCS and can be used for on-road driving for avoiding discrete obstacles, or for off-road driving for avoiding untraversable regions. Examples of untraversable regions are holes, ditches, rocks, trees etc. Since it is infeasible to process all range images within a given time to avoid latency problems, attention is focused on important regions within the image. Currently, this is done by predicting which regions of future images will contain the most useful information based on current images and the current world model [6]. The proposed metric can be utilized for such prediction by facilitating the comparison and detection of images that contain information unchanged from previous views. Thus the metric enables the *prediction of expected information utility* of an action.

For UGVs to react appropriately to moving objects in dynamic environments, we have developed a Moving Object Representation, Prediction, and Planning System [10]. Within this framework, as soon as a sensor image becomes available, the proposed metric can facilitate in the

[3] During thresholding, although it is possible that in certain images no histogram peaks may correspond to unique features in the environment, there exist image processing techniques by which either the original intensity values can be transformed to a new image such that the pixel brightness in the new image represents some derived parameter such as the local brightness gradient or direction [16] or by deriving measurement parameters of features from images at many threshold levels [19].

development of a traversability criterion by evaluating expected new information. This in turn enables to determine which parts of the terrain are traversable, thus resulting in planning safe paths through the terrain.

V. Conclusions and Further Research

In this paper, we have presented an entropic information metric to evaluate information content of sensed images. This was accomplished by constructing an image-specific histogram, and using image intensity levels, the corresponding information contained in the sensed images was evaluated. Entropy was shown to be an intuitive measure for evaluating and ultimately utilizing sensor measurements for several robotic navigation tasks in accordance with the RCS hierarchical architecture. Since the information metric provides a scalar value, it is a suitable representation for decision making.

Continuing research efforts will concentrate on formally verifying the concepts developed in this paper on UGVs. Sensor data from field trials on the XUV will be used to refine the applicability of the proposed metric within RCS.

A notable area of further research is to extend the ideas developed in this paper towards information theoretic descriptions of visual spatial and geometric features of color images. Another area that we are investigating is the extension of the information metric to 3D scenes where instead of the number of pixels, the number of voxels are considered.

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