Vision-Based Terrain Classification and Solar Irradiance Mapping for Solar-Powered Robotics

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Abstract—This paper examines techniques for real-time terrain classification and solar irradiance mapping for outdoor, solar-powered mobile robots using a vision-based Artificial Neural Network (ANN). This process is completed sequentially. First, terrain classification is completed by extracting key features from visual-spectrum images captured from an on-board camera using Haar wavelet transform to identify both color and textural information. These features are then classified using an ANN to identify grass, concrete, asphalt, gravel, and mulch. Using the terrain classes, the image is then analyzed using concepts from high dynamic range imagery to establish the solar irradiance map of the area. In this way, our sequential methodology presented allows unmanned vehicles to classify the terrain and map the irradiance of a given area with no prior knowledge. Whereas, the terrain classification can be used in determining energy consumption or traversability criteria and the irradiance map can be used to estimate the energy harvesting capabilities.

Index Terms—Field Robotics, Image Processing, Solar Mapping, Terrain Classification, Solar Robotics

I. INTRODUCTION

Unmanned ground vehicles (UGVs) have been ubiquitously applied in many fields due to their particular aptitude in a variety of applications, such as surveillance and reconnaissance, sensing and mapping, and cargo hauling. Many of these missions require vehicles to be able to traverse rough or hazardous terrain that is potentially unknown to the vehicle a priori for extended periods of time. It is because of this that researchers have focused on extending unmanned vehicles’ capabilities to work in a wide range of environments and operate for prolonged mission durations. While each of these tasks are of equal importance, they are usually investigated separately. This work aims to improve the vehicle’s situational and energy awareness by using a sequential visual-based terrain classification and solar mapping technique. By developing these techniques, solar-powered UGVs will have the capability to sense and classify their environments, both in terrain types and solar energy harvesting capabilities. This information can then be provided to existing mission planning algorithms for better optimization of mission critical variables, such as time, energy expended or objectives accomplished.

Identifying the environment in which the UGV is operating allows UGVs to maintain safe operation and extend their mission capabilities. In literature, there are two key areas of identification: terrain classification and terrain characterization. In terrain characterization, the goal is to define the traversability of the terrain. The goal in terrain classification, however, is to define the types of terrain such as grass, gravel, or soil. One approach to terrain characterization is using sensors commonly equipped on UGVs, like a differential measurement unit, to extract the frequencies of the vehicles terrain induced vertical acceleration and a Probabilistic Neural Network (PNN) classification algorithm [1]. Alternatively, by integrating a vision system, a mobile robot can use the imagery data obtained to identify key terrain traversability characteristics, such as roughness, slope, discontinuity, and hardness [2]. Another approach [3] proposes terrain characterization to determine traversability, which uses Gray Level Co-occurrence Matrices (GLCM) to extract textural features from images gathered by the UGV.

Terrain classification is commonly achieved using on-board imaging process. Work in [4] introduced a Neural Network method for classifying terrain, such as sky, grass, foliage, pavement, soil, or gravel, based on color, texture, and spatial features of an image, using discrete wavelet transform coefficients by means of the Daubechies 2 wavelet in the HSI color space. Instead of visual imagery, it has been proposed [5] that radar data can be used to classify terrain into three classes (1) scatter to represent porous volumes, (2) linear to capture thin objects, and (3) surface to capture solid objects. It has also been proposed that both terrain classification and characterization can be done simultaneously using a neural network and features gathered by on-board sensors such as inertial sensors, motor sensors, etc. [6].

Once the desired terrain features are known, the objective then becomes extending the operational capabilities of the vehicle. Long-term operation has been recognized as a point of interest in the robotics community. Attempts to extend a vehicle’s operational time have, in a large part, focused on the selection of efficient components [7] and the use of efficient path planning [8]. Recently, a more novel approach to extending mission duration is to incorporate renewable energy sources, such as solar energy, to charge storage batteries as backups for sustained operation [9]–[11]. Examples of how solar power can increase mission time includes, but not limited to the Mars Opportunity Rover [12], which has explored unknown areas on Mars for ten years, and the “cool robot” designed to carry payloads during the summer months in the Antarctic [13]. These missions are characterized by uniform energy conditions, however, in many scenarios, the environment will have non-uniform energy density. Being able to properly map and navigate these areas as to take full
advantage of the solar power has yet to be fully researched. Our previous work has shown that if the solar energy of an area is known, various missions can be planned to significantly improve mission performance by avoiding shadowed areas [14]–[16]. Therefore, an efficient and precise method of determining the solar energy distribution of an area is critical in mission planning of solar-powered UGVs.

Commercial software such as ArcGIS [17] can construct digital elevation maps from aerial photographs, which can be used to construct rough radiation maps through ray-tracing, though this is of little help to a vehicle operating in unknown environments. One of the earliest methodologies of generating a solar energy map in real time onboard a UGV presented was the TEMPEST mission-level planner that determines the angle of the sun and implemented a raytracing strategy to estimate the shape of nearby terrain and solar map [18]. An alternative method [19] was developed that uses Gaussian Process (GP) regression to build a solar map using a current sensor and GPS. Later work [20] suggested that the GP regression worked well over short time scales, but is computationally expensive for many sampling points and is difficult to extend the approach accounting for changing sun position and intensity during the day. Thus, the authors instead chose to use a raytracing strategy to develop the solar maps. Our previous work [16] demonstrated the ability of a visual-spectrum image to be used in an indoor setting to produce a solar map in front of a UGV. However, this method was limited to indoor or uniform surfaces. While all of the aforementioned methodologies are able to produce solar energy maps, they lack robustness and ability to be used without prior knowledge of the environment, restricting the environments the vehicles can operate, or require the vehicle to have already traversed the given area. Thus, there is currently no viable option to generate solar maps in a robust fashion in a wide range of applications, such as in unknown environments or in rapidly changing environments. Thus, it is apparent that there is a need for an efficient methodology to generate solar energy maps in these given circumstances.

This paper presents a sequential approach of handling the terrain classification and solar irradiation mapping using visual-based techniques. The organization of the paper is as follows. The proposed methodology of terrain classification is introduced in §II, followed by the development of the solar irradiation mapping in §III. We then present verification data of our methodologies in §IV. Conclusions with final remarks are addressed in §V.

II. TERRAIN CLASSIFICATION

In this section, the terrain classification algorithm is introduced. As has been discussed previously, it is common to take one of two approaches to visual-based terrain classification: wavelet feature extraction or GLCM. Authors in [21] performed an analysis of these methodologies and found that the Haar wavelet had lower time complexity and higher accuracy of classification as compared to other wavelets and GLCM. The efficiency of wavelet feature extraction compared to GLCM is not surprising as there are known issues of the computational burden associated with GLCMs [22]. However, in this work, we determined that GLCM outperformed a standard wavelet feature extraction methodology in terms of classification accuracy. In order to take advantage of the GLCM accuracy and the wavelet feature efficiency, we propose to perform a wavelet analysis; however, instead of using more traditional wavelet features, such as mean, energy, and standard deviation, it was elected to use the textural features described by [23] that were designed to be used with a GLCM.

The algorithm is composed of two stages, as shown in the top part of Fig. 1. The first stage of the algorithm is the offline training. In this stage, the ANN is trained to recognize the various terrain types. The second stage is the online classification process. Both stages include a preprocessing step that segments the image into smaller sections for classification. This is followed by a wavelet transform that is then used to determine Haralick textural features and average color features. These features are then used to either train or classify the segment as a given terrain. Finally, in the online classification, a post-processing and labeling occurs before the terrain classification is complete.

A. Wavelet Transform

For better resolution of the textural information, a two level Haar wavelet is used to extract features from the wavelet domain. While other color frames have been proposed [4], we found it sufficient to simply use the RGB frame. The wavelet transformation using Haar basis function is demonstrated in Fig. 2, where the sub-band images are defined as \( B_k \) and the LL is the approximate detail image, HL is the horizontal detail image, LH is the vertical detail image, and HH is the diagonal detail image.

![2-level Haar wavelet transform](image)

Fig. 2: 2-level Haar wavelet transform
Each of the sub-bands have resolution in each color channel and are usually analyzed using the mean and energy values, which can be found as,

\[
B_k^{\text{Mean}} = \frac{1}{N} \sum_{i=1}^{N} |c_i^k| \tag{1}
\]

\[
B_k^{\text{Energy}} = \frac{100}{E_{\text{total}}} \sum_{i=1}^{N} (c_i^k)^2 \tag{2}
\]

\[
E_{\text{total}} = \sum_{k=1}^{K} (c_k^k)^2 \tag{3}
\]

where \( N \) is the total number of wavelet coefficients of each
sub-band and $K$ is the total number of sub-bands. However, upon analysis of the mean and energy of each sub-band, it was determined that they were very noisy for the data sets that were gathered for training and analysis, which was also observed by the authors in [4]. Because of this, they were not used in the training or analysis to generate an ANN for terrain classification. Instead, a synthesized channel from each sub-band is generated, thus generating a weighted ANN for terrain classification. Instead, a synthesized channel was not used in the training or analysis to generate an 

The cluster shade determines the skewness of the coefficient matrix, meaning it measures the symmetry of the matrix. A high cluster shade typically denotes a non-symmetric image. $B_k^{\text{Cluster Shade}} = B_k^{H5} = \sum_{i,j} (i-M_x + j - M_y)^3 c_{syn}^k(i,j)$. (9)

where $M_x = \sum_i \sum_j i c_{syn}^k(i,j)$ and $M_y = \sum_i \sum_j j c_{syn}^k(i,j)$. Lastly, the maximum probability is a measure of the maximum intensity within the coefficient matrix.

$B_k^{\text{Maximum Probability}} = B_k^{H6} = \max(c_{syn}^k(i,j))$. (10)

For this work, we only used the $B_0$ sub-band since others had larger noise and the efficiency/performance was very promising. In this way, the features determined are $F_{\text{Haralick}} = [B_0^{H1}, B_0^{H2}, B_0^{H3}, B_0^{H4}, B_0^{H5}, B_0^{H6}]$. (11)

2) Color Features

In order to include more terrain classification features, color information is also used. For this work, we investigated RGB, HSI, and LAB color frames; however, the LAB frame was computationally inefficient and the RGB performed better than the HSI in both color and textural information. Thus,
the color features of a segmented image can be determined by
\[ F_{Cn} = \frac{1}{N} \sum_{i} \sum_{j} I(i, j, n). \]  
(12)

where \( I \) is the \( R, G, B \) image, \( n \) represents the channel of color. In this case, \( R, G, B \) channel respectively.

3) Feature Vector

Finally, there are 9 features that are used to characterize the terrain, 6 textural and 3 color. The entire feature array can be defined as,
\[ F = [F_{Haralick}, F_{C}]. \]  
(13)

C. Artificial Neural Network Classifier and Training

In order to solve the non-linear pattern terrain classification problem, we constructed an ANN in MATLAB. The neural network used 15 hidden layers and log-sigmoid activation function. The input layer consisted of a 9-dimensional feature vector. The output layer consisted of 6 classes corresponding to the six terrain types of interest: grass, concrete, asphalt, mulch, gravel, and dirt. A general structure for neural network is shown in Fig. 3, where in our case there are \( N = 15 \) hidden layers, \( F = 9 \) features and \( C = 6 \) classes.

![Fig. 3: Structure for an N layered neural network with F features and C classes](Image)

Training of the ANN was completed by using two training images, or 15,000 training segments, for each class of terrain. The weighting parameters were computed using a Levenberg-Marquardt training, which updates the weight and bias values using back-propagation according to Levenberg-Marquardt optimization. This process is iterated until the performance goal is met or until the performance has stopped improving, which is denoted by the minimum performance gradient threshold, set as \( 10^{-7} \).

D. Post Processing

While the ANN classifier presented in the paper works well on its own, it does misclassify some terrain segments within a given region. Because of this, a smoothing algorithm that examines the region surrounding each segmentation is used. This algorithm examines the immediate region around each segment and determines the mean, mode, and standard deviation of the terrain types. If a given segmented image is outside a \( 3 - \sigma \) bound, then it is likely that it was misclassified. The algorithm then analyzes the mean and mode to determine the proper terrain type for the segment. The process and output are shown in Fig. 4, where \( A, B, \) and \( C \) represent the actual image, the direct output from the ANN, and the output after post processing, respectively.

![Fig. 4: Post processing procedure: A. Actual image, B. Output from ANN, and C. Output after post processing](Image)

III. Solar Irradiance Mapping

In this section, the solar irradiance mapping algorithm is introduced. This algorithm takes advantage of high dynamic range imagery concepts in order to determine relative irradiance of a given image that can then be mapped to absolute irradiance through a calibration gain constant. This algorithm is also composed of two stages, which is illustrated in the bottom part of Fig. 1. The first stage is the offline calibration stage. This calibration is performed in two steps. First, a camera response function is determined using high dynamic range images to determine a relationship between pixel intensity and radiance values. Next, the calibration gain constant is determined through experimental testing to understand the relationship between relative and absolute irradiance values. It should be noted that this calibration only needs to be completed once for a given camera, since it is the final mapping of the electronics and will remain constant even as time of day/year or geographical location change. While in the online stage, images are mapped from the image plane to the actual scene to provide a solar irradiance map of the environment captured.

A. Background

There are multiple relationships that need to be identified in order to generate solar irradiance maps from images captured from a digital camera. These key relationships, which are outlined in the bottom part of Fig. 1 (highlighted with red boxes), occur as the solar light is traced from its source to the camera sensors. As light hits a surface, it is reflected off the surface as radiant flux. The incoming light is known as irradiance, denoted as \( E_s \), representing the scene irradiance (measured as the power per unit area \( W/m^2 \)). After reflecting off the surface, it is known as radiance, denoted as \( E_a \) (measured as power per steradian per unit area \( W/steradian/m^2 \)). It is this value that is required to be determined in our analysis, as it will determine the amount of solar energy available to be harvested from the environments. Based on the type of surface, the amount of radiant flux that is reflected will change. This mapping from irradiance to radiance is the first relationship and can be expressed as,
\[ L_a = \frac{\rho \tau E_s}{\pi} + E_{diffuse}. \]  
(14)

where \( \rho \) is the reflectance of the surface, which can be determined based upon the wavelength of the light, \( \tau \) is the angle in terms of steradians, and \( E_{diffuse} \) is the irradiance diffused in the atmosphere before hitting the surface, which is typically defined as 10% of the direct solar intensity [24].

Next, an image is taken of the surface. The light gathered by the image is from the surface radiance reflected off the surface. Before reading the photometric sensors, the light first passes through the camera lens. As the light passes through
the lens, the light is mapped from the scene radiance, \( L_s \), to the image irradiance, \( E_I \). This mapping is a proportional mapping and known from the properties of the lens. Based on the camera’s lens characteristics, there will be variation in the irradiance across the film plane. This can be determined analytically based on the following equation [25],

\[
E_I = L_s \left( \frac{\pi}{4} \right) \left( \frac{\cos^4(\alpha)}{m^2} \right)
\]  

(15)

where \( E_I \) is the image irradiance, \( L_s \) is the scene radiance, \( m \) is the \( f \)-number of the lens, and \( \alpha \) is the pixel’s angle from the lens’ optical axis. It should be noted that the effect of \( \alpha \) is assumed to be small given the lens size. Also, most modern camera lenses are designed to compensate for this mapping process [26]. It is shown here for completion of the theoretical development.

Lastly, after passing through the lens, the light passes through the camera electronics, where the image irradiance is mapped to the measured pixel values, which is defined as the pixel intensities, \( I_P \). This final mapping is non-linear and dependent upon the camera being used and the settings of the camera. For any camera model and settings, there exists a camera response function that relates image irradiance at the image plane to the measured pixel intensity values, \( g : I_P \rightarrow E_I \).

In this way, there are a total of three mappings that take place: (1) scene irradiance to scene radiance, (2) scene radiance to image irradiance, and (3) image irradiance to measured pixel values. The first mapping is well defined and if the surface is known then a database developed by NASA can be used to determine the bidirectional and directional hemispherical reflectance properties [27]. The second mapping has a known analytical solution, expressed in Eqn. (15), and is handled by the digital cameras. Finally, the third mapping needs to be determined experimentally. The process for this mapping is detailed in [26]. We will describe our implementation, which follows the process outlined in [26], and include a calibration to determine the absolute irradiance as compared to a relative irradiance. Finally, it should be noted that for the rest of the paper, the maps generated will have the units of \( W \) and not \( W/m^2 \), which is the unit for irradiance. This is because our calibration data was taken using a testbed rover that utilizes a solar panel to measure \( W \). While the units are different, the two values are directly comparable, given converting from irradiance to watts is done based on the area of the solar panel.

### B. Response Curve Mapping

When a digital camera takes an image of a scene, it stores the information in terms of pixel values. In order to understand the radiance map of the scene captured, the nonlinear relationship must be identified [26]. Each camera has a response function that relates irradiance, \( E \), and the measured pixel value, \( Z \). However, it is difficult to find a relation because the pixel values are not directly related to irradiance. We utilize the same relation equation between these properties as demonstrated in [26]

\[
g(Z_{ij}) = \ln(E_i) + \ln(\Delta t_j)
\]  

(16)

where \( i \) ranges over pixels, \( j \) indexes over exposure times \( \Delta t_j \), \( E_i \) is scene irradiance over pixels, \( Z \) is pixel values, and \( g \) is response curve. A single image has a limited dynamic range. Thus, in order to fully understand this nonlinear relationship, multiple images taken with various exposure times are needed in order to develop a highdynamic range set of images. This is shown in Fig. 5 (a).

![Fig. 5: (a) High dynamic range images and (b) camera’s response curve](image)

Using the full dynamic range of the camera, the camera’s response curve that relates exposure time and pixel values to the radiance can be defined using Eqn. (16). The response curve of the camera used in this work is shown in Fig. 5 (b).

Once the curve \( g \) is determined, any image can be converted to an irradiance map as long as the exposure time is known and the camera’s parameters are equivalent to those used when gathering the high dynamic range images. While the process of determining the response curve uses multiple images, it is computationally expensive to use in a real-time system. Therefore, a single image is used at a single exposure time. Then, the irradiance map is expressed as,

\[
\ln(E_I) = g(Z_{ij}) - \ln(\Delta t_j)
\]  

(17)

Figure 6 shows a reconstructed radiance map from a captured image, since it is known that the camera handles the conversion from irradiance to radiance directly.

![Fig. 6: Conversion from an image to a radiance map: (A) Image and (B) Radiance map](image)

### C. Scene Radiance to Scene Irradiance

Once a radiance map is generated from an image, the last mapping is to convert scene radiance to scene irradiance, which is defined in Eqn. (14). Since the surface will be determined from the ANN terrain classification process, a simple database is used to determine what the reflectance properties of the surface are. This database is developed by NASA and available for a wide range of surface and takes into account both bidirectional and directional hemispherical reflectance properties of surfaces across a wide range of wavelengths of light in [27]. An example reflectance curve for grass is presented in Fig. 7.
Using the reflectance properties for each wavelength acquired within the image, the scene irradiance map can be determined. The output from this process is shown in Fig. 8.

D. Post Processing

As was done with the ANN classifier in §II D, the irradiance maps are smoothed to remove anomalies and to create a smooth, continuous map. This process is done in multiple stages. The first is to remove pixels with large anomalies both high and low. These do not occur very often, but could be caused by a surface not being classified properly or larger/smaller than predicted reflectance properties. Next, the image is smoothed based on regions as was completed with the ANN classifier. Lastly, the image is smoothed using a moving average filter. The process and output are shown in Fig. 9.

E. Irradiance Calibration

As described above, the process thus far will only provide the user with relative irradiance values. Since there is no way of gathering absolute irradiance values without a precise sensor, such as a pyranometer, which only measures the solar irradiance over a small area, it is necessary to determine the relationship between the measured relative irradiance to the absolute irradiance. In order to determine this relationship, it was selected to gather a map of the given area using a precise measuring tool. In previous papers, we presented a methodology of gathering a solar map using a rover taking samples at discrete locations in a gridded pattern [14]. The same approach was taken where an image was taken and then the same area was mapped using an experimental testbed rover with a solar panel attached, however, it should also be noted that this could also be accomplished with just a solar panel, battery, and solar charger, such as a maximum power point tracker (MPPT). The rover was used since it had all the necessary components installed. The same process will be used in §IV for validation purposes. In this way, we are able to determine a gain constant to relate relative to absolute irradiation values. This process is shown in Fig. 10 and is only completed once in the offline calibration stage.

IV. EXPERIMENTAL RESULTS

With the eventual goal of this work to be implemented on board a solar robot, we used a small-sized digital camera (Canon PowerShot S100 [28] with an ISO 100 and f/8) that would be easily integrated into many robotic systems. In this section, we will discuss the experiments that were performed to both benchmark and validate our methodologies presented in this paper. We will first benchmark and validate our ANN terrain classifier. This will be followed by a validation of the irradiance mapping and sequential process for multiple types of environments. The irradiance mapping process does not have a separate section as it requires the ANN classifier output to perform it in the field. All images presented were taken at either Iowa State University or The Ohio State University.

A. Terrain Classification

To begin, the ANN classifier presented in this paper was designed to be computationally efficient and accurate on a wide range of terrains. Many previous papers have discussed methodologies on terrain classification using a wide range of feature sets including, but not limited to, color (RGB, HSI, LAB, etc.), GLCMs and Haralick texture features, spatial features, and wavelet features. When developing our method, we went through a large number of feature sets to identify features that best capture the differences in the terrains of interest. We explored different color spaces, GLCMs with Haralick texture features, wavelet features, and Haralick texture features using wavelet coefficients. Given space constraints, we present a few methods to benchmark and validate our methodology. The first comparison method is using RGB color and GLCMs and Haralick texture features, spatial features, and wavelet features. When developing our method, we went through a large number of feature sets to identify features that best capture the differences in the terrains of interest. We explored different color spaces, GLCMs with Haralick texture features, wavelet features, and Haralick texture features using wavelet coefficients. Given space constraints, we present a few methods to benchmark and validate our methodology. The first comparison method is using RGB color and GLCMs and Haralick texture features, which will be noted as RGB/GLCM. The next comparison method uses HSI and wavelet features for texture, which will be noted as HSI/WF. This is trained similar to [4], but does not include spatial features. An analysis of 4 images, shown in Fig. 11, was conducted to compare the methodologies to determine performance.

The results indicate that the RGB/GLCM and HSI/WF perform fairly well with 82.81% and 80.11% accuracy, respectively. However, as shown in images 2 and 3 of Fig.
Fig. 11: Experimental results using a variety of feature sets. The color code is as follows: grass - green, mulch - red, concrete - blue, gravel - yellow, asphalt - black, dirt - brown.

11, neither of these methods are able to classify the gravel. Instead, both methods classify gravel as mulch. Although this is the case, our proposed feature set using wavelet coefficients and Haralick texture features is able to properly classify a majority of the gravel present in the same images. This can be seen in the average classification rate as well, where our method has a 90.42% classification accuracy. Finally, it should also be noted that our proposed method has a much reduced computational time when compared to the RGB/GLCM and HSI/WF. The RGB/GLCM had an average computation time of 30.8 seconds. The HSI/WF had an average computation time of 11.72 seconds. Our method, however, had an average computation time of 5.63 seconds. These computation times are based on using an image resolution of 4000x3000 and done in MATLAB on a MacBook Pro with a 2.3 GHz Intel Core i7 processor.

B. Sequential Classification and Mapping Process

Finally, we validate the ability of these methodology presented in §II and §III to be performed sequentially, as is shown in Fig. 1. In this way, we will further validate the ANN classifier and the calibration process shown in §III D for the irradiance mapping. This illustrates the effectiveness of the algorithms as well as how they will be implemented in practice. In order to showcase the full potential of the sequential process developed. Five images were selected to validate this process with various types of terrains and shading effects as seen in Fig. 12. The first four images show a singular type of terrain, grass (1-2) and asphalt (3-4) respectively, in the image. While the last image (5) contains two different types of terrains was taken to validate that the irradiance mapping will produce equivalent values for various terrains contained within the same image. All images and maps were gathered on February 12, 2018 between 2:30pm and 3:00pm on The Ohio State University campus.

First, in terms of the irradiance mapping performance, given there are not any other available benchmarks aside from using raytracing or a Gaussian process to predict an energy map, the experimental data sets were gathered using the same methodology presented in §III D. It can be seen that the proposed method matches the ground truth image in terms of predicted power available. It also verifies that our proposed method offers better resolution over a map generated in a gridded pattern. In order to quantify the accuracy, it was selected to compare the gathered data points to the predicted power at each point. Of the images taken, the maps generated by the camera were within an average of 3.61% of the measured data. Lastly, in terms of accuracy performance, the ANN terrain classification obtained a classification rate of 94.89%. This validates that our methodology presented in this paper can handle multiple types of terrains and shading conditions and produce accurate terrain and irradiance maps.

V. Conclusion

This paper presented a real-time, sequential terrain classification and solar irradiance mapping process designed for outdoor, mobile solar robots using a vision-based Artificial Neural Network (ANN). Our terrain classification ANN implemented an efficient and accurate wavelet and Haralick texture features that outperformed more conventional methodologies presented in existing works. Using the terrain information from the ANN, we introduce a new methodology of generating irradiance maps that extends work focusing on High Dynamic Range imagery. Future work will include two major components. The first one is further development of the ANN terrain classifier, specifically increasing accuracy, efficiency, and recognition of more terrain types, such as dry grass and leaves, as it can be seen that dead grass is currently classified as mulch. Second, the methodology will be integrated in real-time mission planning for outdoor solar-powered robots.
Fig. 12: Experimental validation using multiple surfaces and shading conditions. The color code is as follows: grass - green, mulch - red, concrete - blue, gravel - yellow, asphalt - black, dirt - brown.

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