2018 IEEE Signal Processing Cup

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ECE-498: Capstone Design Project

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REPORT SUMMARY

The goal of this Senior Capstone Project is to lead Union College's first ever Signal Processing Cup Team to compete in IEEE's 2018 Signal Processing Cup Competition. This year's competition is a forensic camera model identification challenge and is divided into two separate stages of competition: Open Competition and Final Competition. Participation in the Open Competition is open to any teams of undergraduate students, but the Final Competition is only open to the three finalists from Open Competition and will be held at ICASSP 2018 in Calgary, Alberta, Canada. Teams that make it to the Final Competition will be competing to win a grand prize of $5,000. The goal of this year's competition requires teams to build a classification system that uses a combination of various signal processing, machine learning, and image forensic techniques in order to determine the make and model of the camera used to capture a digital image both before and after that image has been post processed. IEE has provided teams with and image database consisting of ten different camera models and 275 images accompanying each camera for which competing teams to use to build their classification systems. This senior project design report focuses on the proposed classification system design that will be implemented and submitted on behalf of Union's Signal Processing Cup Team. The chosen classification system design uses methods of re-sampling and re-interpolating in order to build a feature space based on the relative differences of the original and reconstructed images from the provided image database and to then use this feature space to train and test a machine learning classifier algorithm. Through the completion of this project, students competing in the IEEE Signal Processing Cup will gain experience using signal processing, machine learning, and image forensic techniques to solve challenging information security problems.

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1. Introduction

Over the past decade, the presence and usage of multimedia and digital content in peoples' everyday lives has become especially prevalent all around the world. However, this rise in the global usage of digital content in almost every aspect of society was accompanied with the rise of various methods used to alter and falsify this information. In order to combat this rise in content counterfeiting, techniques such as encryption have been developed in order to maintain information security across different communication links in a network [1]. However, these encryption techniques cannot prevent the manipulation of multimedia content before encryption occurs. Therefore, the consequences of digital content manipulation are still a problem in society today, but, in many cases, information forensics can be used to uncover these undetected falsifications. The field of information forensics is concerned with determining the authenticity, processing history, and origin of digital multimedia content based mainly on the digital content itself [1]. Image forensics is a subset of this field of information forensics and is focused exclusively on determining the trustworthiness of digital image content. As it becomes easier and easier for people in society to create realistic forgeries of images and videos, the need for determining the origin and authenticity of this content increases as well.

This year's IEEE Signal Processing Cup competition focuses in on this field of image forensics and poses a challenge of solving the problem of determining an image's true origin: the camera identification challenge (Figure 1) [2].

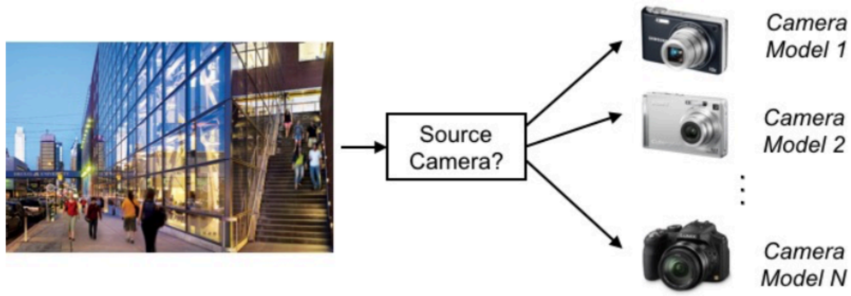

FIGURE 1: SOURCE CAMERA IDENTIFICATION CHALLENGE [2]

Information about the type of camera used to capture an image can explicitly provide an answer to this origin question as well as provide an effective method of applying these classification methods in several real-world situations. The classification system that teams are required to build for the Signal Processing Cup competition needs to be able to receive an image as an input and use their trained classifier to determine the make and model of the camera used to capture that image [2]. The scale on which these classifications systems will be operating is limited to a specified range of just ten different camera models, so the application of these classification systems will be restricted as a result. However, the classification methods used in each system can be directly and effectively applied to more complex systems that are required to classify more extensive camera model subsets, thus enhancing the applicability of this year's Signal Processing Cup competition to the world of information forensics.

The rest of this report is organized as follows: section two will cover an overview of several techniques that have been applied to solving this camera identification challenge along with the potential impacts of this identification challenge on various present-day health and safety, social, political, and ethical issues; section three will cover the detailed design specifications provided by the 2018 IEEE Signal Processing Cup challenge, the overarching functional decomposition of the project, and the selection of the design criterion for the final system design; section four will present several different detailed design alternatives and the reasons behind the final design choice for this project; and section five will present the preliminary proposed design of this project in its entirety with as much detail as possible.

2. Background Information

2.1 Camera Identification Context & Previous Work

An essential part of developing a classification system for digital content is developing unique signatures for each content source. These signatures are constructed through the analysis of intrinsic fingerprints that are left over in the content itself as a result of different content processing steps [1]. This allows for not only the ability authenticating content's origin but also the ability to trace back the content's processing history. In respect to the goals of this project, the unique signatures for each camera model can be developed through inspection and analysis of a digital camera's internal processing pipeline (Figure 2).

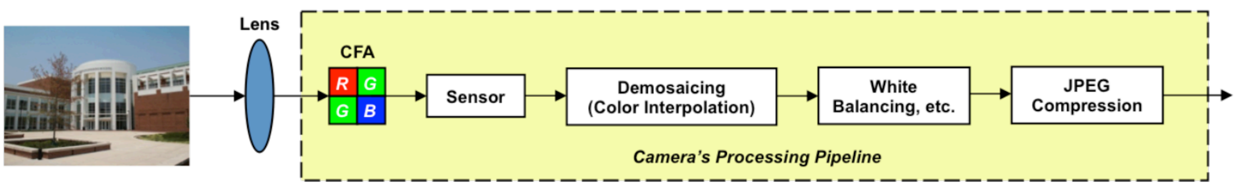

Figure 2: A Typical Digital Camera's Internal Processing Pipeline [2]

As shown in Figure 2, light enters the camera through a lens, which focuses light on an optical sensor. This light passes through a color filter array (CFA) that is located between the lens and the sensor. The CFA is an optical array that only allows for one color-band of light to reach the sensor at each pixel location. Thus, the image constructed by the optical sensor is missing the remaining two color-bands at each pixel location and must then interpolate the missing information. This process of color interpolation is known as demosaicing. After this process, the image may then be further processed internally through various color balancing and JPEG compression processes depending on the specific camera [2]. After all of these internal processes, the output image is produced.

As mentioned above, each of these internal processes within the processing pipeline in a digital camera imprints its unique intrinsic footprint contained within the final output image and can therefore each be used to develop unique signatures for specific camera models. Research has been conducted in the past that has used the different fingerprints from a camera's processing pipeline to build a classification system that attempts to tackle this camera identification problem. For example, it is possible to model and estimate the demosaicing filter used by a camera or to capture pixel dependency values introduced by the demosaicing process by developing several forensic algorithms [3], [4], [5]. The make and model of an image's source camera can be determined using statistical models of sensor noise and other noise sources [6], [7]. Also, during JPEG compression, traces are left behind by proprietary quantization tables [8]. Additionally, camera model traces can be captured using statistical techniques from steganalysis [9] and heuristically designed feature sets [10].

Thus, it is possible to construct a "fingerprint" for that camera model with this forensic information from many images taken from a specific camera model. Several fingerprints are then constructed for each camera model in question and are used as classification features when training a machine learning algorithm to recognize an image's source camera model.

2.2 Potential Impacts on Present-Day Issues

The camera identification challenge has a number of implications on present-day health and safety, social, political, and ethical issues. First of all, the ability to determine the authenticity of images can positively impact the health and safety of society. Images are often used as evidence in criminal investigations, which include investigations regarding blackmail, child exploitation, homicide, and many others. In each of these cases, it would be essential for the criminal investigators to know if all of the data present shown in an image is authentic and as well as determining from where these images came with a certain amount of confidence. The application of these camera identification techniques would be helping to ensure the safety of the victims involved in these specific criminal cases. On a broader note, the military and defense agencies of a nation could use these techniques to verify the authenticity and origin of images used as intel for different scenarios. Consequently, techniques for camera identification would be helping to either maintain or improve national health and security depending on the nature of the situation.

The significant presence that the media has in people's everyday lives makes the effects of these camera identification techniques especially impactful in a positive way. With the almost universal availability to image editing and fabricating software, the likelihood of counterfeit images being spread through the media is relatively high, especially if these images are as realistic as the originals. This causes the incredibly-persuasive media to sometimes spread fake news through a huge population of media followers, which could potentially influence the opinions and reactions of viewers to this false information. The amount of influence that the media has on the general public substantially increases the need of filtering out this false information in the form of counterfeit images. This filtering process is where these camera identification techniques would have the greatest impact and, therefore, help increase the likelihood of the spread of truthful information to a society.

The spread of counterfeit information through the media to the general public also can have a direct effect in politics as well. Much of politics relies on elections based on the popularity of various politicians, so as one can imagine, having a relatively-well-respected reputation is essential to having a successful political career. Any information that could negatively impact a politician's reputation would unfairly set that person at a disadvantage depending on the severity of the information. In order to reduce the spread of this fake news, such as realistically-fabricated images for example, it would be positively impactful to have systems in place that could help filter out this information. And, as for the case of filtering out counterfeit images, implementing these camera identification techniques would be especially useful.

However, on a more negative side of things, these camera identification techniques could also present some ethical problems. Camera identification techniques can be used to uncover similarities between the internal processes of different camera models, thus exposing possible cases of intellectual property theft [5]. However, if it is possible to expose possible intellectual property theft using these techniques, then it also must be possible to commit intellectual property theft using these techniques as well. While the act of committing or attempting to commit intellectual property theft is a definite ethical crime, the act of watching this event take place also presents a serious ethical issue. For example, if a camera development engineer witnesses his coworker or supervisor using camera identification techniques to steal processing techniques from a rival camera company, then this camera development engineer would be at the crossroads of a significant ethical dilemma. Either he or she puts his or her job at risk by making the ethical decision to either speak up against this act or to threaten quitting, or he or she makes the unethical decision to keep his or her mouth shut and go along with the criminal acts. This is a very difficult ethical decision for any professional engineer to make, but situations like these have a chance of coming up during one's career and he or she must be prepared to do what is right. Thus, although the general application of these camera identification techniques might not introduce ethical issues, more specified applications of these techniques could unveil some serious ethical issues.

3. DESIGN REQUIREMENTS

The design requirements for this project have been specifically outlined in the 2018 Signal Process Cup competition document provided by the IEEE Signal Processing Society, the sponsors of this competition [2]. The overall goal of this year's Signal Processing Cup competition is to build a system capable of identifying the camera make and model used to capture a digital image. The competition is comprised of two stages of competition: Open Competition, which is open to any eligible team of undergraduate students, and Final Competition, which is open only to the three finalists of the competition.

3.1 Open Competition

The Open Competition is divided into three separate parts for this year's Signal Processing Cup: Part 1, Part 2, and the Data Collection Task. The Data Collection Task of Open Competition will be left out of this project because it requires teams to gather 250 images from a camera not provided in the original dataset and, therefore, has no effect on the overall design of the classification system that makes up this report. The deliverables for Open Competition are due January 21, 2018.

3.1.1 Open Competition – Part 1

For Part 1 of Open Competition, teams are provided with a dataset with which to use to build and train their camera model identification systems. The dataset is comprised of ten different camera models along with 275 images for each camera model, totaling 2,750 images at teams' disposal. In order for teams to evaluate their classifier systems, a new evaluation dataset will be released approximately two weeks prior to the January 21 submission deadline. This evaluation dataset will be comprised of images captured using devices different from those used to create the training dataset. This will require teams to build a camera identification system that correctly classifies all devices of a particular camera make and model – not to the specific devices used to capture the images in the training dataset.

3.1.2 Open Competition – Part 2

For Part 2 of Open Competition, teams are required to determine the make and model of cameras used to capture images that have been post-processed. Examples of image post-processing include JPEG-recompression, cropping, contrast enhancement, etc. So, for this part of Open Competition, teams will have to build a camera identification system similar to Part 1 that is fine-tuned to classifying post-processed images. In order to build their classification systems, teams will be provided with a list of all possible post-processing operations that will be considered along with a Matlab script that can be used to generate post-processed images from the original dataset of unaltered images. Upon generating their own post-processed image dataset, teams will then need to use this as a training dataset with which to build their camera identification systems. And, again, as in Part 1, teams will be provided with an evaluation dataset approximately two weeks prior to the January 21 submission deadline.

3.1.3 Open Competition – Deliverables

The following material must be submitted by the January 21, 2018 deadline in order to be considered for the Final Competition [2]:

1. A report in the form of an IEEE conference paper describing the technical details of the system.

2. Camera model identification results from Open Competition.
3. Data Collection Task.
4. An executable with a Matlab implementation of the camera model identification system. This should be able to accept an input in the form of a directory of images and produce a text file identifying the camera model used to capture each image in the directory.

3.2 Final Competition

The three finalists that compete in the Final Competition of the Signal Processing Cup are chosen by a panel of judges based on the overall quality of each team's submitted report and each team's overall accuracy of each team's camera model identification systems. Accuracy is determined using the following equation:

$$\text{Accuracy} = \left(\frac{\text{Number of images with correct camera model identifications}}{\text{Total number of images}}\right) \times 100$$

The overall accuracy score is determined by combining each accuracy score from Open Competition using the following equation:

$$\text{Score} = \ 0.7 \times \text{Part 1 Accuracy} + 0.3 \times \text{Part 2 Accuracy}$$

So, the three teams with the highest overall scores and highest quality reports will be competing at the 2018 International Conference on Acoustics, Speech, and Signal Processing (ICASSP) for a chance to win the grand prize of $5,000.

3.3 Functional Decomposition

Overall, despite the different requirements from each part of the competition, the overarching goal remains the same: build a camera identification system that can determine the make and model of a camera used to capture a given digital image. In order to do this, teams must use various image forensic and signal processing techniques in order to construct a feature space with which to train a machine learning classifier algorithm that will ultimately make the final camera identification decision. This basic functional decomposition is shown in Figure 3 below.

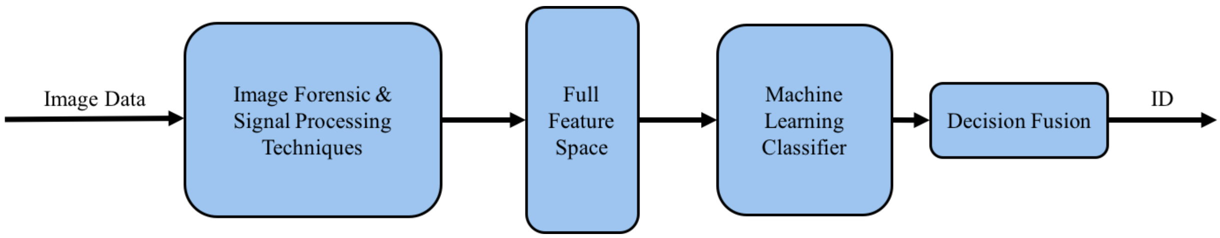

FIGURE 3: FUNCTIONAL DECOMPOSITION OF CAMERA MODEL IDENTIFICATION SYSTEM

The final system must be able to read an input of a directory of images, extract the desired information from the image, associate this information with a determined camera model fingerprint, and then output the appropriate predicted camera model identification information.

3.4 Design Selection Criteria

Given these broad design specifications that were provided with the 2018 Signal Processing Cup document, it was then necessary to establish a certain list of criteria by which to further refine the design process of the camera model identification system for this project. The list of criteria is listed below:

1. Image forensic/signal processing techniques must be straightforward enough such that the system design could be well explained to Union's Signal Processing Cup Team.
2. Classification techniques used in final design must have proven success in similar case studies from published sources, i.e. greater than 90% average camera model accuracy.

The first criterion comes in respect to the fact that this project includes leading Union's Signal Processing Cup Team in this year's competition. Since Union's team is comprised of undergraduate students with varying levels of signal processing experience, the final design choice must be intuitive enough that the specific functionality of the design can be easily explained to all team members. The second criterion establishes a filtering method while researching possible classification techniques to solve this camera model identification challenge. This restricts the focus of possible final designs to camera classification systems that have been implemented with average camera model accuracy of at least 90%. Keeping these criteria in mind, it was next possible to narrow the possible design selections to a select handful of possibilities.

4. Design Alternatives

Along with the 2018 IEEE Signal Processing Cup competition document, the IEEE Signal Processing also provided teams with several supplementary references to learn about the camera model identification challenge. A majority of these references presented different methods of solving this challenge, so the goal of this research was to deduce which methods were going to be the best to implement based on the established design selection criteria in Section 3.4. The design selection process used deductive reasoning to eliminate some possible methods from final design contention.

Some possible design alternatives were noise-based methods, which use statistical models of sensor noise and other noise sources to identify the make and model of an image's source camera [2]. The sensor noise model, otherwise known as the photo-response non-uniformity (PRNU) model, can reliably identify a specific camera, and was proven to do so in [6]. The other noise model mentioned above is the heteroscedastic noise model, which can be used to describe a natural raw image [7]. The first issue with these models was the relatively high likelihood of developing a classifier that over fit the classification of the camera models to each of the specific devices used to construct the image database. This would result in a classifier that had almost perfect training accuracy but would perform very poorly when it had to classify images captured using different devices of the same camera makes and models as provided in the image database. In addition to this potential design flaw, the statistical models used in both of these noise-based camera identification models were incredibly dense. This presented the difficult challenge of being able to understand the models well enough to not only implement them in our own system but also to be able to easily teach them to the other team members of

Union's Signal Processing Cup team. These two points were key factors in ruling out using a noise-based classifier system design for this project.

After ruling out a noise-based classifier design, the next best option was a demosaicing-based classifier. Out of all of the studies provided as references by the IEEE Signal Processing Society, three of them were studies showing the effectiveness of a demosaicing-based classifier: two studies attempted to identify specific CFAs and demosaicing algorithms in order to solve this camera identification challenge, and the third study was the study selected as the basis of design for this project's camera model identification system. The first of these studies used techniques aimed at determining the parameters of CFA and demosaicing algorithms, but however were only able to achieve an overall accuracy of 90% [3]. The accuracy of this system was the lowest of the three demosaicing studies presented, so it was then eliminated from final design contention. The second of these studies aimed at using techniques to identify sixteen different demosaicing algorithms, with which to then use as a way of identifying a camera's make and model to an average overall system accuracy of 98.3% [4]. The only flaw to this design, which was the eventual reason for elimination from final design contention, was the relative complexity of the classification methods used. Compared to the final design used in this project, which is based off of the design used in [5], the overall accuracies of the systems were almost equal; however, the final design chosen for this project was much more straightforward and easier to understand than the design used in [4]. Thus, this comparison of designs made the ultimate decision for the final design for the camera identification system to be based off of the design used in [4].

5. Preliminary Proposed Design

The preliminary proposed design for this project is based off of the design of a general camera identification system design that was explained in [5]. The authors of this paper used an demosaicing-algorithm-based classifier and were able to obtain an average classification accuracy of 99.2% for their system. The proposed design for this report's specific camera model identification system is outlined below.

5.1 Image Forensic Techniques

The camera model identification system design proposed uses three image forensic techniques in order to construct a full feature space for the classifier: a Bayer CFA filter, demosaicing algorithms, and co-occurrence matrices.

5.1.1 The Bayer CFA Pattern

A color filter array (CFA) is typically a 2x2 repeating pixel pattern that allows only one color component of light to pass through it at each location before the light reaches the sensor (Figure 4) [2].

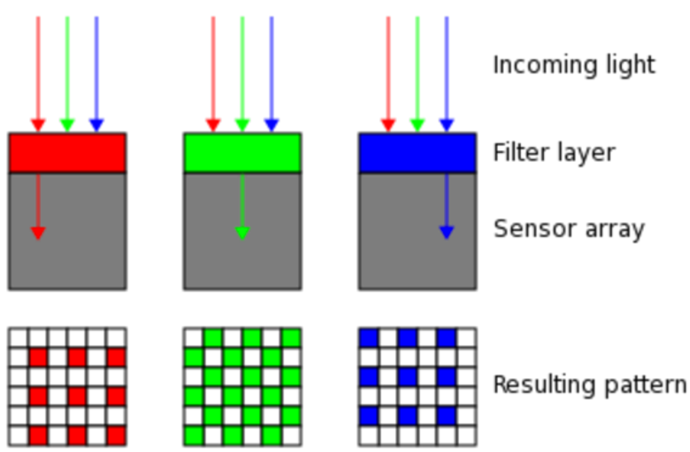

Figure 4: Example CFA Pattern Operation [11]

Out of all the CFA patterns, the Bayer pattern (Figure 5) is the most commonly used.

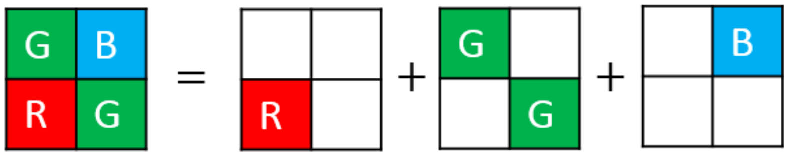

FIGURE 5: THE BAYER CFA PATTERN

The Bayer CFA 2x2 pixel filter pattern can be oriented in four different ways: GBRG (Figure 5), GRBG (Figure 6), BGGR (Figure 4), and RGGB. As a result of this process, as seen in Figures 4 and 5, the resulting image is missing the remaining two color components at each pixel location, which requires a process of color interpolation, called demosaicing, to fill in the remaining color components.

5.1.2 Color Interpolation (Demosaicing)

As described above, the process of demosaicing is the process of interpolating the remaining two unobserved color values at each pixel location. A complete methodology on how this method of color interpolation works is shown in Figure 6.

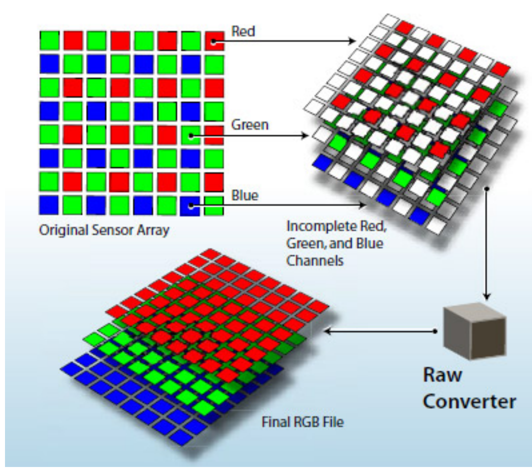

FIGURE 6: THE BEFORE AND AFTER RESULT OF THE DEMOSAICING PROCESS [12]

The demosaicing process shown in Figure 6 is the process that occurs at the step which is labeled "Raw Converter," which converts this raw image from the sensor into a complete image, i.e. the demosaicing process. This process is implemented through the use of a demosaicing algorithm. Some examples of demosaicing algorithms include nearest neighbor interpolation, bilinear interpolation, and smooth-hue interpolation [13].

5.1.3 The Co-occurrence Matrix

Co-occurrence matrices are used to capture pixel value dependencies introduced by the demosaicing process [2]. Specifically, the authors of [5] use co-occurrence matrices to observe the frequency at which certain color channel dependencies occur within each 2x2 pixel frame within the image. For example, Figure 7 shows an example of a geometric structure used to build a co-occurrence matrix of the red channel, and Figure 8 shows a similar geometric structure used to build a co-occurrence matrix of the red-green channel.

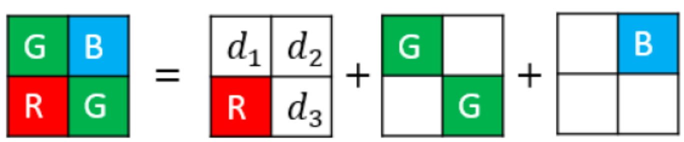

FIGURE 7: EXAMPLE GEOMETRIC STRUCTURE FOR BUILDING RED CHANNEL CO-OCCURRENCE MATRIX [5]

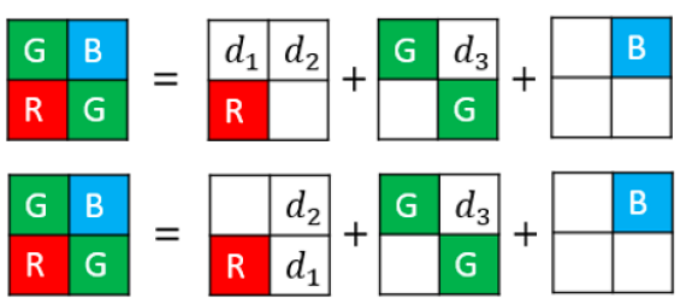

FIGURE 8: EXAMPLE GEOMETRIC STRUCTURE FOR BUILDING RED-GREEN CHANNEL CO-OCCURRENCE MATRIX [5]

Each of these figures show a single instance of their respective generated co-occurrence matrix where the values (d_1, d_2, d_3) are compared to their respective locations in each pixel frame. Thus, these matrices capture pixel value dependencies based on specific color channels of interest.

5.2 Feature Space Construction

The above three image forensic methods are used sequentially in order to construct the full feature space for this camera identification system. A general architecture for this feature space construction is shown in Figure 9.

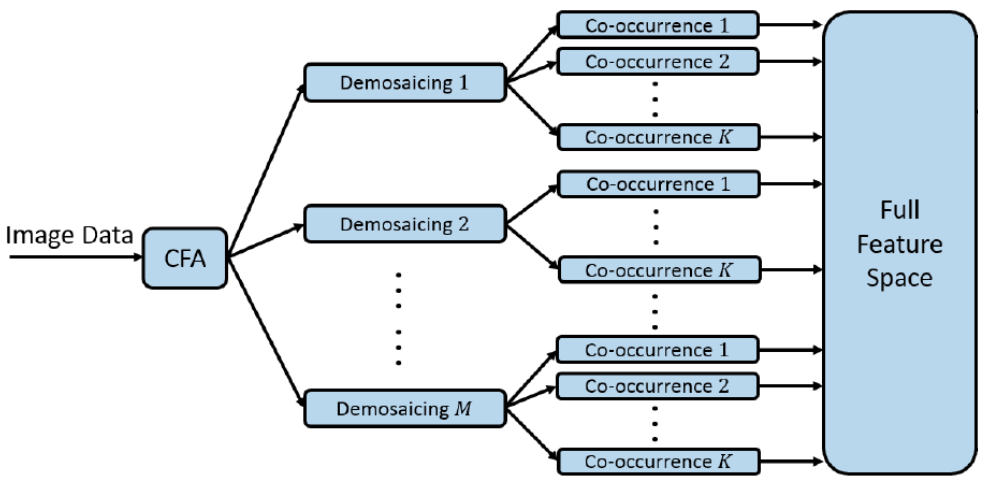

FIGURE 9: FULL FEATURE SPACE CONSTRUCTION ARCHITECTURE [5]

Figure 9 highlights the role that each of these information image forensic techniques play in developing the full feature space for this proposed classifier design. In this design, the image data is re-sampled and re-interpolated to create reconstructed images. The reconstructed images are subtracted from their original images creating "error" images. These error images are then compressed in such a way that they are able to be analyzed using co-occurrence matrix evaluations. This resulting co-occurrence matrix information makes up the full feature space of this classifier system. A more detailed explanation of these steps is defined below.

5.2.1 Image Re-sampling

The first step towards feature space construction for this proposed design is a re-sampling of the image data using a CFA pattern. In this proposed design, the specific CFA pattern used is a Bayer pattern in GBRG format (as seen in Figures 5, 7, and 8). Other Bayer pattern formats can be used for the re-sampling step, but the GBRG format was chosen because it is the same format used in [5]. This is important because the co-occurrence matrix calculations provided are very complex and are based on this specific Bayer pattern format. This allows for an easier application of the provided co-occurrence matrix calculation equations into this project's camera identification system design and implementation.

5.2.2 Image Re-interpolating

The next step of feature space construction is using demosaicing to reconstruct the image data from the raw image data provided by the CFA filter in the previous step using demosaicing. At this point in the construction architecture, there are multiple demosaicing algorithms to choose from here – specifically, there are six algorithms: Nearest Neighbor Interpolation, Bilinear Interpolation, Smooth Hue Transition Interpolation, Median-Filter Bilinear Interpolation, Gradient-Based Interpolation, and a Gradient-Corrected Linear Interpolation. Any combinations of these demosaicing algorithms could be implemented to greatly increase the full feature space size.

5.2.3 Error Image Construction and Compression

Once the image data has been reconstructed, the error image data must be constructed and compressed. Figures 10 and 11 present the necessary pseudocode to complete both of these tasks, respectively.

$$\mathbf{E} = \mathbf{X} - \mathrm{Demos}_{CFA,H}(\mathbf{X})$$

FIGURE 10: PSEUDOCODE FOR CALCULATING ERROR IMAGE DATA [5]

$$\mathbf{E} \leftarrow \mathrm{trunc}_T\left(\mathrm{round}\left(\frac{\mathbf{E}}{q}\right)\right)$$

FIGURE 11: PSEUDOCODE FOR COMPRESSING ERROR IMAGE DATA [5]

The pseudocode in Figure 10 shows the calculation of a single error image by means of subtracting a reconstructed image, $Demos_{CFA,H}(\boldsymbol{X})$, from the original image, $\boldsymbol{X}$. The reconstructed image here was constructed using a specified CFA pattern and demosaicing algorithm H. Following this step, the error image is then compressed by means of quantization and truncation as shown by Figure 11. Here, $T = 3$ and $q = 2$, which are the same values used for these equations in [5]. This compression method divides all of the current values in $\boldsymbol{E}$ by 2, rounds the resulting values to the nearest integer, and then truncates any values larger than 3 and smaller than -3 to each of these values, respectively.

5.2.4 Full Feature Space Construction

Once the image data is in this form, it can then be analyzed effectively through the use of co-occurrence matrices. As provided by [5], there are two co-occurrence matrix evaluations to choose from at this point: a red channel evaluation and a red-green channel evaluation. The following pseudocode in Figure 12 shows the construction of the separate RGB channels from the error image data.

$$\begin{aligned}\mathcal{G}1 &= \{(i,j)|i\ odd, j\ odd\}\\ \mathcal{B} &= \{(i,j)|i\ odd, j\ even\}\\ \mathcal{R} &= \{(i,j)|i\ even, j\ odd\}\\ \mathcal{G}2 &= \{(i,j)|i\ even, j\ even\}\end{aligned}$$

FIGURE 12: PSEUDOCODE FOR GENERATING RGB COLOR CHANNELS GIVEN GBRB BAYER CFA [5]

Having consolidated the separate color channels, it is then possible to implement the co-occurrence matrix calculations for the red channel (Figure 13) and the red-green channel (Figure 14).

$$\begin{aligned}&\mathbf{C}^{(R)}_{CFA,H}(d_1,d_2,d_3) =\\ &\frac{1}{|\mathcal{G}1|}\sum_{(i,j)\in\mathcal{G}1}\mathbb{1}\Big((\mathbf{R}_{i,j},\mathbf{R}_{i,j+1},\mathbf{R}_{i+1,j+1}) = (d_1,d_2,d_3)\Big)\end{aligned}$$

FIGURE 13: PSEUDOCODE FOR GENERATING RED CHANNEL CO-OCCURRENCE MATRIX [5]

$$\begin{aligned}&\mathbf{C}^{(RG)}_{CFA,H}(d_1,d_2,d_3) =\\ &\frac{1}{|\mathcal{G}1|}\sum_{(i,j)\in\mathcal{G}1}\mathbb{1}\Big((\mathbf{R}_{i,j},\mathbf{R}_{i,j+1},\mathbf{G}_{i,j+1}) = (d_1,d_2,d_3)\Big)\\ &+\frac{1}{|\mathcal{G}2|}\sum_{(i,j)\in\mathcal{G}2}\mathbb{1}\Big((\mathbf{R}_{i,j},\mathbf{R}_{i-1,j},\mathbf{G}_{i-1,j}) = (d_1,d_2,d_3)\Big)\end{aligned}$$

FIGURE 14: PSEUDOCODE FOR GENERATING RED-GREEN CHANNEL CO-OCCURRENCE MATRIX [5]

These co-occurrence matrices are counting up the number of times the specific combination of (d_1, d_2, d_3) occurs within the specified pixel frame for all pixel frames in an image and then normalizing them for every combination of (d_1, d_2, d_3). These resulting matrices from each constructed error image from each re-interpolated image from each demosaicing algorithm make up the full feature space for this proposed camera model identification system design.

5.3 Machine Learning Classification System

The specific machine learning classification algorithm for this identification system has yet to be chosen, so an explicit definition of the design of this section is unavailable. However, despite which machine learning algorithm is chosen, the same classifier training process occurs from the system feature space. In order to determine the overall accuracy of one of the possible classification combinations, the feature space is broken up into a training feature space and a testing feature space. This enables the construction of a confusion matrix for a given feature space in order to present the accuracy of the current system across each of the ten cameras involved. In order to pick the best machine learning classifier for this specific application, it will be necessary to conduct trial-and-error with a provided toolbox of algorithms to see which algorithm provides the best results. The selection of the final machine learning algorithm will ideally be completed by the end of this upcoming winter break.

5.4 Final Classification Design Decision

The final classification design system will be an implementation of a certain combination of the available six demosaicing algorithms with the two available co-occurrence matrix algorithms. In order to find the perfect combination of algorithms for this specific camera identification challenge, each algorithm combination will need to be tested and each resulting confusion matrix output from the machine learning classifier will have to be compared. Finding the ideal feature space for this specific application will be the most challenging part of the design process because of the relatively large availability of different classification algorithms in this proposed design.

6. References

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