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gbsv Mini-Challenge 2

Nils Fahrni

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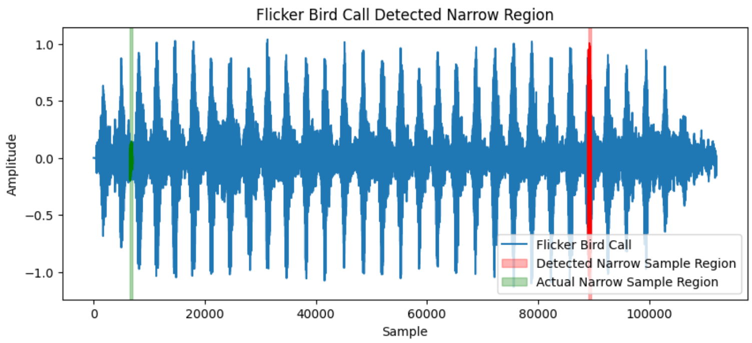
1 Notable Results

In this project, we explored various aspects of Image and Signal Processing through a series of meticulously designed experiments. The key findings are summarized below:

Correlation in Signals

In the first Task I delved into signal correlation analysis using autocorrelation and cross-correlation methods. Specifically, I analyzed the calls of the Northern Flicker, a bird native to the Pacific Northwest. This bird's calls, characterized by unique and repetitive patterns, were ideal for autocorrelation analysis, allowing us to visually display the periodicity of these patterns.

This task also included an exploration of cross-correlation by extracting a segment of the bird call and identifying it within the larger signal. This helped me understand how minor variations, such as noise, didn't affect the detection within the original signal. However, choosing a too narrow sample can result in a faulty detection.



Segmentation

In the second part I tried to segment objects in two cases:

Bear Segmentation

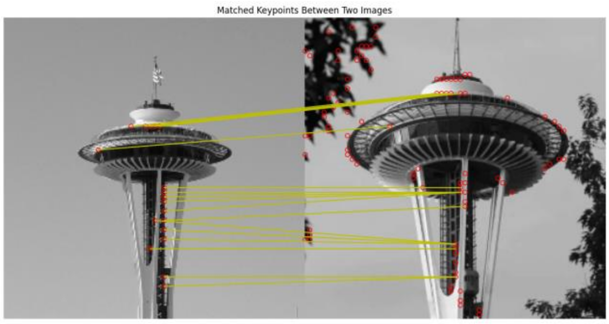
The segmentation of bears provided a unique challenge due to their complex shapes. In that case I used Otsu's Method to separate the background from the bears. Furthermore, I applied morphological operations that removed the remains in the background which didn't belong to the bears. The result was quite good when considering that no segmentation model was applied.

Tree Segmentation

In a second example I wanted to bring a more real-world use-case to life by segmenting trees from a neighborhood's aerial view. This would hypothetically allow a town's administration to monitor the health of the greenery. This time I didn't base the segmentation on contrast but on color. For that I utilized the HSV Color Space to find bounding colors that best separated the trees.

Keypoint Matching

The Keypoint Matching part (Task 3) was the least satisfying part, though the learnings out of this can be viewed as notable. In this task I tried to match keypoints of different viewpoints of the Space Needle in Seattle. The applied Keypoint Descriptor "Histogram of Oriented Gradients (HOG)" is quite good when it comes to interpretability of an image's keypoints but it is practically useless when images of different viewpoint angles are to be matched. Keypoints can be matched if the change in angles is very small.



2 Discussion

Autocorrelation in Signals:

Advantages: Autocorrelation is a useful technique for analyzing bird chirping signals due to its ability to effectively detect periodicity. It is relatively simple to implement and provides valuable insights into the time-lag relationships within the signal. Additionally, autocorrelation is known for its robustness, maintaining effectiveness even with slight variations in the signal characteristics.

Limitations: Autocorrelation faces challenges when dealing with signals, which are inherently non-stationary and exhibit rapid frequency changes. This leads to potential inaccuracies in capturing the signal's periodicity and frequency variations. Moreover, autocorrelation can be computationally demanding for long signals and sometimes yields ambiguous results, particularly with complex or overlapping chirps. Though there are also approaches which make use of the Fourier Transform to find the A Its limited frequency resolution further constrains its effectiveness in detailed frequency analysis.

Comparison with Expectations: I expected the correlation to be high whenever chirps overlap each other and therefore low whenever the overlaps don't match, this is also the result that was yielded and further on visually explored in the notebook.

Cross-Correlation in Signals:

Advantages: Cross-correlation between a signal and a sample window within that signal is an insightful method for signal analysis. It excels in identifying the degree of similarity and the time-lag relationship between the sample window and different segments of the signal, which is crucial for time-shifted signal pattern recognition. Moreover, cross-correlation can be adapted to varying window sizes, making it versatile for analyzing signals with different characteristics. It also was found to be relatively robust even if the underlying signal is noisy.

Limitations: Its important to carefully choose a sensible sample window as it can be too small and therefore correlate with too many ambiguous lags inside the signal.

Comparison with Expectations: The initial sample window could be found within the original sample. I would've expected the cross-correlation to struggle more with added noise but I was surprised that it barely had impact next to just raising the overall correlation – which is expected. I could imagine, that of course, if the amount of added noise exceeds a certain threshold the cross-correlation will be less robust.

Threshold-Based Segmentation:

Advantages: By enhancing contrast and applying a calculated threshold, Otsu's method effectively differentiates between background and foreground, making it ideal for images with distinct contrast differences. This method is particularly efficient in situations where the objects and background have clear grayscale intensity differences. Moreover, its automatic threshold calculation simplifies the process, eliminating the need for manual threshold setting, which can be subjective and inconsistent.

Limitations: The threshold-based segmentation technique using Otsu's method has limitations, especially in images with low contrast or similar grayscale values between the object and the background. In such cases, the method may fail to accurately distinguish between the two, leading to poor segmentation results. Furthermore, it may not perform well in images with high levels of noise, as noise can significantly alter grayscale intensity levels, affecting the threshold determination. Additionally, this method assumes a bimodal histogram (two distinct peaks representing foreground and background), which is not always the case in complex images, limiting its applicability. For example, in my case with the bears, there was no clear underlying bimodal distribution of intensities, though the grayscale image already brought a relatively clear separation to the table.

Comparison with Expectations: Not only Otsu's Method was applied but also numerous morphological operations. Surprisingly enough, the sequential appliance of these operations kept the shapes of the bears in place well even though their shapes are complex. A resulting observation sadly was that the snout of the bears couldn't be segmented correctly as the brown bears had bright fur on that part of their body. Without manual/local operations in these parts there was no way to preserve that part of the head.

Color-Based Segmentation:

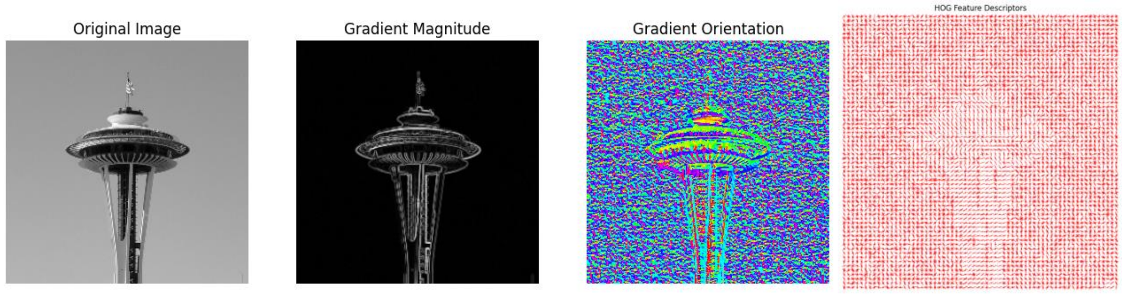
Advantages: Color-based segmentation, particularly in the HSV (Hue, Saturation, Value) color space, showed to be an effective technique for distinguishing between different objects in images, such as separating trees from houses in the proposed Google Earth imagery. The HSV space's separation of color information (hue) from intensity (value) allows for more accurate and intuitive segmentation of colors like the green of the trees' leaves, making it suitable for such scenes. This method is obviously useful in scenarios where color is a distinct and consistent feature of the objects of interest, as it can reliably differentiate between objects based solely on color characteristics.

Limitations: This approach also has some limitations. Color-based segmentation can be sensitive to lighting conditions and shadows, which might alter the perceived color in an image, leading to inaccurate segmentation. Additionally, in complex scenes where object colors are not uniform or are similar to background colors, distinguishing between them can be challenging. For example in the tree segmentation process multiple trees that had a touching crown could sometimes not be segmented properly without the application of techniques like the "Euclidean Distance Transform".

Comparison with Expectations: I expected to have a harder time segmenting only the trees from the Google Earth Photograph as the trees often times stand on patches of grass along sidewalks or front yards. With the help of morphological operations and area-based thresholding I was able to get rid of most of the grass patches that didn't belong to trees. Throughout the process though, a lot of tree segments suffered from the many operations (especially the EDT) and lost a lot of information on their actual original shape.

Keypoint Matching with HOG:

Advantages: I found the advantages of the Histogram of Oriented Gradients (HOG) to be a valuable feature descriptor when it is important to visualize the keypoints. The representation I applied in the notebook with the directional line-shapes allowed me to understand quickly how different keypoints can get matched. Its strength especially lies in capturing the object's shape and texture information by analyzing the distribution of intensity gradients or edge directions. This makes HOG particularly robust in different lighting conditions, as it focuses on gradient structures rather than color or intensity.



Limitations: Throughout research of multiple sources I found that the HOG is usually not very well fitted for keypoint matches as the keypoints themselves can look very much different if you don't have the same viewpoint of an object in the images you want to match. I could imagine that it only finds application in keypoint matching where the object is always viewed at the same or similar angle.

Comparison with Expectations: I expected the keypoints to look similar in my images which don't deviate too much from each other, but I was surprised. Even smaller changes in angle yielded strongly different histograms and the keypoints couldn't be matched correctly. In scenarios with a clear background and a clear view on the object (Space Needle) itself and within two images with the same viewpoint, keypoints could be matched in a sensible way.

3 Reflection

Compared to the first Mini-Challenge I was able to dive down deeper into those tasks that I found more interest in because the overall style of tasks were clearer and also a bit less in their requirements. For example, I found a lot of joy when trying to segment the images of the bears. During that process also the idea of the tree segmentation came to my mind as a possible real-world application. I am very eager to further explore this part of signal processing in a future semester in modules like dlbs and del.

I personally found the last task to be the most frustrating one as I would've liked to get better results from the HOG Descriptor but sadly it was not possible due to the fact that HOG has very rigid limitations. When exploring resources on the internet I found close to no applications of HOG in Keypoint Matching but what I found was other methods like SIFT which I would've wished to also get to explore in my Mini-Challenge.

Overall, I really liked the opportunity to again get creative when it comes to the data and similar to the first Mini-Challenge I wanted to theme it after a region I liked. This openness was something that pushed me, even in tasks didn't result in desirable outcomes.

4 Repository

https://github.com/okaynils/fhnw-ds-gbsv-mc2

5 Journal

Day	Description
1	**What have I done today?** On the first day I spent working on this MC I started to gather all data for every task so that I could then discuss the signals with the FE. **What worked out well?** I found a wide variety of signals compatible with my theme of the Pacific Northwest. **Where and what problems did emerge?** After discussing the images with the FE I got told about the possible difficulties that might arise with the bear image I chose initially because of the objects overlapping each other without clear color or contrast differences. **Who or what could help me resolve these problems?** -
2	**What have I done today?** Today I started to work on the first task and almost got done with the base of it entirely. **What worked out well?** I was able to advance fast as we already looked at the Cross-Correlation and Autocorrelation techniques during the Deep Dive, so essentially, it's nothing new.

	Where and what problems did emerge? I wanted to explore edge cases within these techniques but couldn't find too many modifications for the signals that would make sense in the real world to further on explore. **Who or what could help me resolve these problems?** -
3	**What have I done today?** I tried to start working on the segmentation of the proposed brown bear family today. **What worked out well?** I found out about the obstacles that overlapping objects without separable attributes put into my process. **Where and what problems did emerge?** I could not find a way to segment the different bears from each other. I only managed to separate the entire group of bears from the background. **Who or what could help me resolve these problems?** I will try again tomorrow and see if I can find techniques that can help me separate the bears independently. If this won't help I am going to look for another image with bears on it that is more easily separable.
4	**What have I done today?** After yesterday's relatively unsuccessful endeavors I tried different methods today, but I accepted that this image could most likely not be segmented using traditional techniques without a deep learning model. I found another image of a brown bear family which still has the complex shapes of bears on it but already separate on the image. After starting to work on this image I quickly found a way to effectively separate the four bears using Otsu's Method. **What worked out well?** I was relieved to see progress after trying out to segment a difficult image for an entire day. The milestones reached today resulted in an already clear separation of the bears from the background. The next step will be to remove the last few faulty fragments in the background through morphological operations. **Where and what problems did emerge?** As already mentioned, I couldn't find a working solution for my initially proposed image. I was able to proceed after finding another image more suitable for the task. **Who or what could help me resolve these problems?** -
5	**What have I done today?** Today I continued my work on the bear segmentation. I managed to remove all the "non-bear"-fragments through morphological operations and the removal of objects that touched the mask's border. **What worked out well?** The removal of the fragments was straight forward. I found the morphological operations to be the most intuitive technique for this task. **Where and what problems did emerge?** - **Who or what could help me resolve these problems?** -
6	**What have I done today?** Today I was able to finish the bear segmentation. **What worked out well?**

	To finish segmenting the bears I applied a label function that gave each individual object in the image its own class. This worked out well and I haven't run into any mentionable issues. **Where and what problems did emerge?** - **Who or what could help me resolve these problems?** -
7	**What have I done today?** Last night a new segmentation idea came to my mind: Segmenting trees from aerial images. Even though I still must calculate properties on the bear-segmentations I wanted to explore this idea so that's what I did today. **What worked out well?** The nature of the aerial image showed to already separate the trees from the houses and street's concrete by color. Therefore, I started to segment the trees using colors. I haven't found the right color boundaries yet that neglect as much grass patches as possible. **Where and what problems did emerge?** The issue with the image at hand is that not only the trees are green but also the grass patches in the houses front yards and on the sidewalks. **Who or what could help me resolve these problems?** I already did some research on this issue and I noted down that maybe applying the color difference in a different color space might be more helpful.
8	**What have I done today?** Just like mentioned in the preceding journal entry I looked into the color segmentation in other color spaces. The HSV space brought up the best results as it treats the boundaries of the green colors more linearly unlike the RGB space. **What worked out well?** My research from the day before did help me a lot in advancing in this task. I found a quick solution. After applying the color difference in the image there still were some remaining unwanted patches but I was able to remove them through morphological operations. **Where and what problems did emerge?** I lost myself a bit in details during this task as I haven't found the perfect process to keep the shapes of each trees true to original size. **Who or what could help me resolve these problems?** I will set a time limit the next time I work on this process as I already spent a lot of time when trying to solve this issue.
9	**What have I done today?** Today I finally finished the tree segmentation procedure. I managed to additionally implement the skeletonization and measurement of the independent objects. I did this for both segmentation experiments (bears & trees). **What worked out well?** The individual measurements of the objects was straightforward – I was able to use out of the box skimage properties which fastened my process while still being able to understand what these measurements actually mean. **Where and what problems did emerge?** - **Who or what could help me resolve these problems?** -
10	**What have I done today?** Off to the last task today I first watched a very helpful video on the HOG by a

	professor at UC Berkeley that explained the main principles and components of the HOG clearly. This understanding really pushed forward my progress as I was able to implement methods that calculate the components of the HOG (magnitude, orientation and through those the histograms). **What worked out well?** I was able to implement the HOG Feature Descriptor without much problems. Next up will be the Keypoint Matching. **Where and what problems did emerge?** - **Who or what could help me resolve these problems?** -
11	**What have I done today?** I spent the entire day today trying to match the keypoints on my Space Needle images. I implemented a matching procedure that calculates the Euclidian distance (similarity) between the histograms to match them. **What worked out well?** I was able to get results fast and visualize them. **Where and what problems did emerge?** The results are not satisfying to me as only a part of the keypoints get matched correctly. **Who or what could help me resolve these problems?** Through research I already found out that the HOG is a very volatile descriptor if the images are not close to being identical when it comes to angle. I then looked at other descriptors such as SIFT and saw that these use a more sophisticated approach that also can be used in differently rotated images.
12	**What have I done today?** I spent the first half of the day trying to fix or improve the keypoint matching with HOG but sadly couldn't improve it by much. For clarity I implemented a threshold that caps the number of keypoints to only show the ones that have distinctive directions/magnitudes. After that I cleaned up my documentation and some of the plots for the submission. **What worked out well?** I was able to finally find and form conclusions towards the last part and accepted that I probably won't be able to detect keypoints in a better way in my selection of images. The documentation process was straightforward and I encountered no specific problems there. **Where and what problems did emerge?** - **Who or what could help me resolve these problems?** -