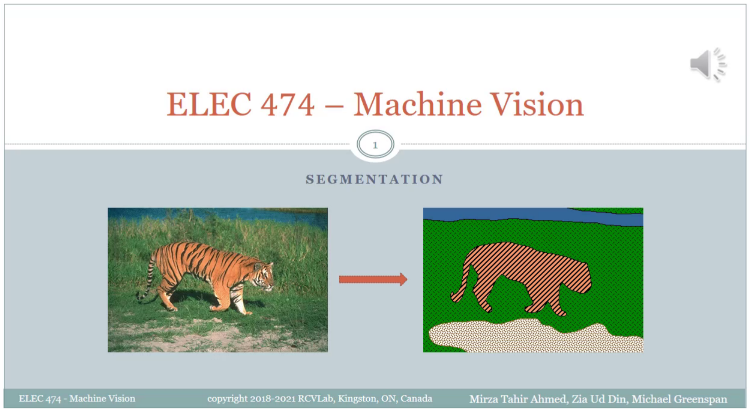
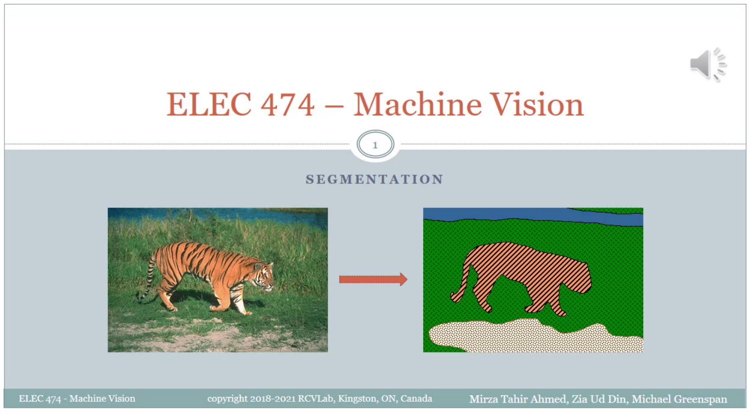
Notes

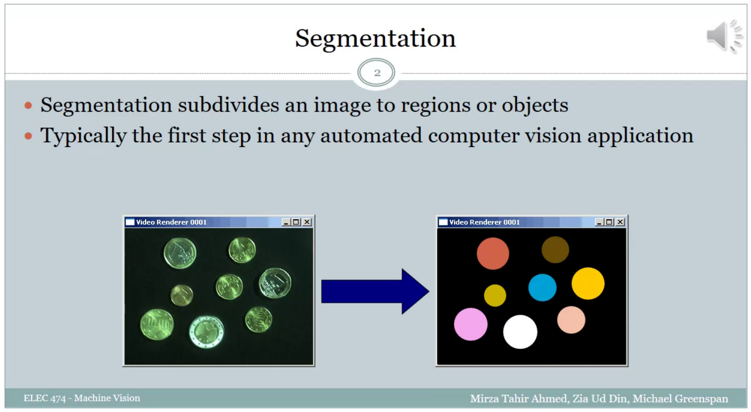
In this lecture, we're going to be looking at the topic of segmentation. So segmentation is a type of processing where we're trying to divide the image into different regions of interest. So, for example, when we take a look at the image on the left, we see a Tiger and we'll see some background grass. And maybe we'll also focus on the river that's in the background. So this is an example of different types of objects, different segments in the image.



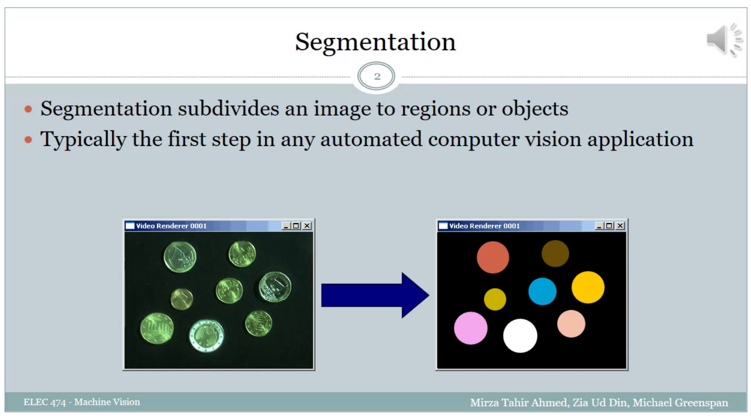
And what we're trying to do with image processing and segmentation is we're trying to define characteristics of these different regions that would allow us to automatically separate these objects into their different segments.



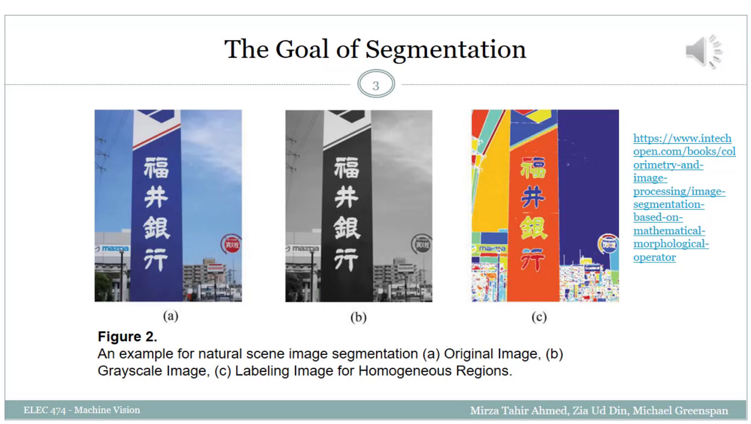
Segmentation is one of those functions that we, as humans perform really effortlessly. And as we'll see computationally, it's quite challenging. And there's a number of different ways to approach this which are interesting. Segmentation is actually really important in many types of automated computer vision applications. So here's an example, for instance, of something like a conveyor belt with coins on it.



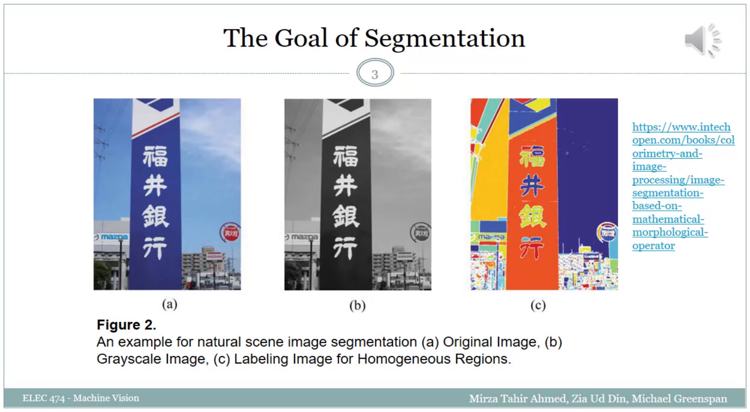
So you can imagine that in an automated processing of this, the first thing we'd want to do is understand where the coins are and where they're not. So that would involve some type of segmentation, which, as we'll see in this particular case, is really easy. But for other types of examples can be quite challenging.



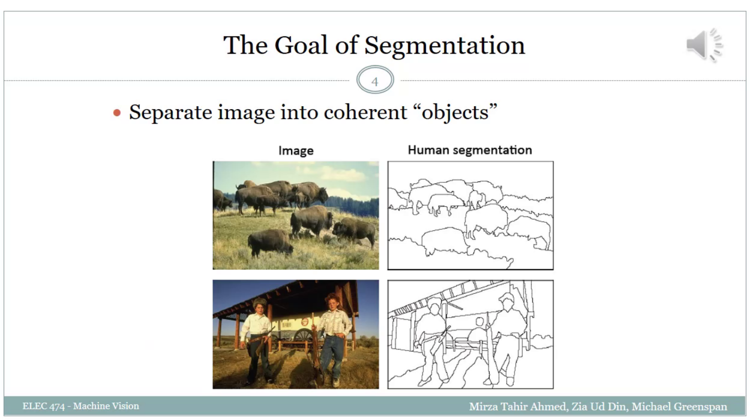
Here's an example of segmentation of a natural image. In the left, in A is the color image, and in the middle, in B is the Grayscale counterpart of that image. And the right and C is the segmented image where a different color represents an individual segment. So you can see it's done a really nice job of segmenting the main elements of this image, which is challenging when you're dealing with a natural image on the bottom of the image on the left and the right bottom, you can see that there's quite a few segments in those areas. And you could argue that this is over segmented, that it's broken the segments into two fine blocks, which happens.



And the other thing that can happen as well with segmentation is you can get an under segmentation where an image is grouped together so that two different segments bleed into each other and become one segment. So those are things that we have to be able to deal with when we're designing a automated computational segmentation method.



The goal of segmentation is to divide the elements in the image into separate objects. Sometimes we think of dividing those into what we call foreground and background objects. So you can think of in these cases, you can think of the Buffalo on the left top image as being the foreground and the grassy plain as being the background. And in the bottom image, you could imagine the two boys standing there as being the foreground and everything else being the background. It's not always entirely clear what is foreground and what is background that's something that is a bit of a judgment call and in fact segmentation itself because it's trying to emulate a human capability is not always obviously cut and dry exactly how the segmentation should proceed.



So one of the things we do to try and gauge the output of a segmentation method is to compare it with human segmentation and there have been experiments where we've taken images like this and we've tasked a set of humans with going ahead and segmenting the image manually into its different distinct segments and will usually give some type of interactive tools to make that a little bit easier so they don't have to go ahead and draw things with a cursor but even then we find that the humans don't always do this exactly the same so segmentation is not a completely well defined task. There's room for interpretation as to what is a good or a bad segmentation and here's an example where the authors of this particular work have done exactly that. They have example input images on the left in a and a version of that in B they have their automatically computationally generated segmentation results in images C and the image D were human made reference segmentations that they used to compare against. So we can see that first of all the human segmentation and the machine segmentation are not exactly the same but there certainly are elements of the machine segmentation which are close to that of the human segmentation so it's always interesting to see how close we can get to human segmentation and that's one of the ways one of the very effective ways that we can compare segmentation auto segmentation against a ground truth result.