ABSTRACT:

**This paper will briefly describe local entropy and local relative entropy thresholding methods and compare them to two studied methods from the literature, those of Kittler and Illingworth and of Otsu.**

INTRODUCTION:

**Local segmentation or thresholding methods have often been found to perform better than global methods due to increased sensitivity to small area features'. The global threshold is based upon some metric computed over the entire image. A threshold derived from such an average response will often fail to segment small objects or objects with similar characteristics to the global background.**

THRESHOLDING METHODS (ПОРОГОВЫЙ МЕТОД):

**Entropy is the measure of the information content in a probability distribution. Relative entropy measures the diiscrepancy between two probability distributions on the same event space. To provide the probability distribution needed for the entropy measures, a co- occui-rence matrix is generated from the input image. It is a mapping of the pixel to pixel greyscale transitions in the image between the neighboring pixel to the right and the pixel below each pixel in the image. From the co-occurrence matrix comes the distribution of greyscale transitions. The candidate threshold divides the co-occurrence matrix into four regions representing within object, within background, object to background, and background to object class transitions. Three entropies, called local, joint, and global, are computed by differing comlbinations of the entropies of this four regions. The relative entropy is cormputed from the transition distributions of the original image and the segmented image.**

**Энтропия - это мера информационного содержания в распределении вероятностей. Относительная энтропия измеряет несоответствие между двумя распределениями вероятностей в одном и том же пространстве событий. Чтобы обеспечить распределение вероятностей, необходимое для энтропийных мер,**

**матрица совместной встречаемости генерируется из входного изображения. Это преобразование пикселя в пиксель переходов оттенков серого в изображении между соседним пикселем справа и пикселем под каждым пикселем изображения. Из матрицы совместной встречаемости происходит распределение переходов оттенков серого. Пороговое значение кандидата делит матрицу совместной встречаемости на четыре области, представляющие переходы внутри объекта, на фоне, от объекта к фону и от фона к классу объекта. Три энтропии, называемые локальной, совместной и глобальной, вычисляются с помощью различных комбинаций энтропий этих четырех регионов. Относительная энтропия вычисляется из распределений переходов исходного изображения и сегментированного изображения.**

**Adaptive Thresholding(local or dynamic thresholding)**

**Thresholding is the simplest way to segment objects from a background. If that background is relatively uniform, then you can use a global threshold value to binarize the image by pixel-intensity. If there’s large variation in the background intensity, however, adaptive thresholding (a.k.a. local or dynamic thresholding) may produce better results.**

**Here, we binarize an image using the threshold\_adaptive function, which calculates thresholds in regions of size block\_size surrounding each pixel (i.e. local neighborhoods). Each threshold value is the weighted mean of the local neighborhood minus an offset value.**

# Image segmentation

**[Image Segmentatio](https://en.wikipedia.org/wiki/Image_segmentation" \t "_blank)**[n](https://en.wikipedia.org/wiki/Image_segmentation" \t "_blank) is essentially the process of partitioning a [digital image](https://en.wikipedia.org/wiki/Digital_image" \t "_blank) into multiple segments to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

**Supervised segmentation:** Some prior knowledge, possibly from human input, is used to guide the algorithm.**Unsupervised segmentation**: No prior knowledge is required. These algorithms attempt to subdivide images into meaningful regions automatically. The user may still be able to tweak certain settings to obtain desired outputs.

# 2) Thresholding

1)Thresholding is used to create a binary image from a grayscale image [[1]](https://scikit-image.org/docs/0.13.x/auto_examples/xx_applications/plot_thresholding.html" \l "id2). It is the simplest way to segment objects from a background.

2)It is the simplest way to segment objects from background by choosing pixels above or below a certain **threshold.**This is generally helpful when we intend to segment objects from their background

Thresholding algorithms implemented in scikit-image can be separated in two categories:

* Histogram-based. The histogram of the pixels’ intensity is used and certain assumptions are made on the properties of this histogram (e.g. bimodal).
* Local. To process a pixel, only the neighboring pixels are used. These algorithms often require more computation time.

Сегментация - важный этап системы распознавания изображений, поскольку она извлекает интересующие нас объекты для дальнейшей обработки, такой как описание или распознавание. ... Методы сегментации используются, чтобы изолировать желаемый объект от изображения, чтобы выполнить анализ объекта.

Region-based Segmentation

**1)We need to convert it into grayscale so that we only have a single channel. Doing this will also help us get a better understanding of how the algorithm works.**

2)This threshold should separate the image into two parts – the foreground and the background.

**3)We will take the mean of the pixel values and use that as a threshold. If the pixel value is more than our threshold, we can say that it belongs to an object. If the pixel value is less than the threshold, it will be treated as the background.**

**Entropy**

In [information theory](https://en.wikipedia.org/wiki/Information_theory" \o "Information theory), the **entropy** of a [random variable](https://en.wikipedia.org/wiki/Random_variable" \o "Random variable) is the average level of "information", "surprise", or "uncertainty" inherent in the variable's possible outcomes. The concept of information entropy was introduced by [Claude Shannon](https://en.wikipedia.org/wiki/Claude_Shannon" \o "Claude Shannon) in his 1948 paper "[A Mathematical Theory of Communication](https://en.wikipedia.org/wiki/A_Mathematical_Theory_of_Communication" \o "A Mathematical Theory of Communication)",[[1]](https://en.wikipedia.org/wiki/Entropy_(information_theory)" \l "cite_note-shannonPaper1-1)[[2]](https://en.wikipedia.org/wiki/Entropy_(information_theory)#cite_note-shannonPaper2-2) and is sometimes called **Shannon entropy**

In information theory, information entropy is the log-base-2 of the number of possible outcomes for a message.

For an image, local entropy is related to the complexity contained in a given neighborhood, typically defined by a structuring element. The entropy filter can detect subtle variations in the local gray level distribution.

In the first example, the image is composed of two surfaces with two slightly different distributions. The image has a uniform random distribution in the range [-15, +15] in the middle of the image and a uniform random distribution in the range [-14, 14] at the image borders, both centered at a gray value of 128. To detect the central square, we compute the local entropy measure using a circular structuring element of a radius big enough to capture the local gray level distribution.

**DataSets**

Набор данных домашних животных Oxford-IIIT - это набор данных изображений домашних животных из 37 категорий, содержащий примерно 200 изображений для каждого класса. Изображения имеют большие различия в масштабе, позе и освещении.

We have created a 37 category pet dataset with roughly 200 images for each class. The images have a large variations in scale, pose and lighting. All images have an associated ground truth annotation of breed, head ROI, and pixel level trimap segmentation.

**Main Models of Information**

A **co-occurrence matrix** or **co-occurrence distribution** (also referred to as : *gray-level co-occurrence matrices* GLCMs) is a [matrix](https://en.wikipedia.org/wiki/Matrix_(mathematics)) that is defined over an [image](https://en.wikipedia.org/wiki/Digital_image) to be the distribution of co-occurring pixel values (grayscale values, or colors) at a given offset. It is used as an approach to texture analysis with various applications especially in medical image analysis

Матрица совместной встречаемости или распределение совместной встречаемости (также называемые: матрицы совместной встречаемости на уровне серого GLCM) - это матрица, которая определяется по изображению как распределение сопутствующих значений пикселей (значений в градациях серого или цветов). ) по заданному смещению. Он используется как подход к анализу текстуры в различных приложениях, особенно в анализе медицинских изображений.

Why would you use co-occurrence matrices?

Whether considering the intensity or grayscale values of the image or various dimensions of color, the co-occurrence matrix **can measure the texture of the image**.

?Because co-occurrence matrices are typically large and sparse, various metrics of the matrix are often taken to get a more useful set of features.

**Table1**

**Эти данные приведены в таблице 1. Оптимальные пороговые значения для каждой меры включены, чтобы дать представление о весе мер.**

**These data are in Table 1. Thresholds optimal for each of the measures are included to give a sense of the weight of the measure.**