DIP NOTES:

Explain Fundamentals of Spatial Filtering

Spatial filtering is a technique used in image processing to enhance, blur, sharpen or remove specific features from an image. The fundamental concept of spatial filtering involves performing mathematical operations on the pixels of an image by using a filter, also called a kernel or mask.

The filter is a small matrix, typically 3x3 or 5x5, which slides across the image and applies a mathematical operation to each pixel it overlaps. The result of this operation is then stored in a new image, which is a processed version of the original image.

The most basic type of spatial filter is the identity filter, which leaves the image unchanged. Another common filter is the smoothing filter, which is used to reduce noise or blur the image. The smoothing filter works by averaging the pixel values in the neighborhood of each pixel.

The sharpening filter is another popular filter, which enhances the edges in the image to make them more prominent. This filter is based on the idea of subtracting the blurred version of the image from the original image, leaving only the edges.

Other common filters include the edge detection filter, which highlights the edges in the image, and the threshold filter, which converts the image to binary by setting pixel values above a certain threshold to white and those below it to black.

Spatial filtering can be used in various fields, including medical imaging, remote sensing, computer vision, and robotics. It is a powerful technique that allows for the manipulation and enhancement of images for various purposes.

Explain The Mechanics of Spatial Filtering

Spatial filtering involves applying a filter or kernel to an image by performing mathematical operations on the pixel values. The filter is a small matrix that slides over the image, and the operation is performed on the pixel values in the local neighborhood of each pixel. The result of this operation is then used to calculate the new pixel value in the filtered image.

The mechanics of spatial filtering involve several steps:

1. Choosing a filter: The first step is to choose the filter to be applied to the image. The filter can be designed to achieve a particular purpose, such as smoothing, sharpening, edge detection, or noise reduction.
2. Sliding the filter over the image: The filter is then slid over the image, with the center of the filter positioned on each pixel in turn. The filter is usually a square or rectangular matrix, typically 3x3, 5x5, or 7x7, although larger filters can also be used.
3. Performing the operation: For each pixel, the filter's values are multiplied by the corresponding pixel values in the local neighborhood, and the results are summed. This calculation is repeated for each pixel in the image. The resulting values are then used to calculate the new pixel value in the filtered image.
4. Updating the image: The filtered pixel values are used to update the corresponding pixels in the new image. This process is repeated for all pixels in the image.
5. Handling the edges: The edge pixels of the image are handled differently than the interior pixels because they do not have a complete neighborhood for the filter to use. Several methods can be used to handle edge pixels, such as extending the image or wrapping the edges around.

Spatial filtering can be performed using different mathematical operations, such as convolution, correlation, or morphological operations, depending on the specific filter and its intended purpose. The choice of filter and operation depends on the specific application and the desired outcome.

How smoothing filters are used for blurring and noise reduction?

Smoothing filters, also known as blur filters, are commonly used in image processing for blurring an image or reducing noise. The basic principle of smoothing filters is to average the pixel values in the local neighborhood of each pixel, which has the effect of smoothing out sharp edges and reducing noise.

The size of the local neighborhood is determined by the size of the filter kernel. A small kernel, such as a 3x3 or 5x5 matrix, is used for mild smoothing, while a larger kernel, such as a 9x9 or 11x11 matrix, is used for more significant smoothing.

There are several types of smoothing filters that can be used for blurring and noise reduction:

1. Gaussian filter: The Gaussian filter is a widely used smoothing filter that uses a Gaussian function to compute the weights for each pixel in the local neighborhood. The Gaussian function gives more weight to pixels closer to the center of the filter, resulting in a smooth and natural-looking blur.
2. Median filter: The median filter is a non-linear filter that replaces each pixel with the median value of its local neighborhood. This filter is particularly effective for reducing noise in images, especially salt-and-pepper noise, which produces randomly placed bright or dark pixels.
3. Mean filter: The mean filter is a simple filter that replaces each pixel with the average value of its local neighborhood. This filter can be used for mild smoothing or noise reduction but can produce a loss of detail in the image.
4. Bilateral filter: The bilateral filter is a non-linear filter that smooths the image while preserving the edges. This filter uses a combination of spatial and intensity weights to calculate the smoothed value of each pixel, resulting in a smoother image with preserved edges.

Smoothing filters are often used in combination with other filters, such as edge detection filters, to achieve the desired result. The choice of filter depends on the specific application and the type of image being processed.

what are Effects of smoothing filters as a function of filter size?

The effect of a smoothing filter on an image as a function of the filter size depends on the specific filter used and the properties of the image being processed. In general, increasing the size of the filter results in more smoothing or blurring of the image, but it can also result in a loss of detail and sharpness.

When a smoothing filter is applied to an image, it replaces each pixel with an average or weighted average of its surrounding pixels in a local neighborhood. The size of this neighborhood is determined by the size of the filter kernel, and increasing the kernel size includes more pixels in the neighborhood.

If the filter size is too small, the smoothing effect may be insufficient to reduce noise or blur the image effectively. On the other hand, if the filter size is too large, the image may become overly blurred or lose critical detail.

The effect of a smoothing filter on the image as a function of filter size can be summarized as follows:

1. Small filter size: A small filter size, such as a 3x3 or 5x5 kernel, results in mild smoothing, but it may not be sufficient to reduce noise or blur the image significantly.
2. Medium filter size: A medium filter size, such as a 7x7 or 9x9 kernel, results in moderate smoothing and can effectively reduce noise and blur the image while preserving some details.
3. Large filter size: A large filter size, such as an 11x11 or 13x13 kernel, results in significant smoothing or blurring of the image, which can reduce noise but also lead to a loss of detail and sharpness.
4. Very large filter size: A very large filter size, such as a 15x15 or larger kernel, results in excessive smoothing and can make the image appear blurry and lose important details.

In summary, the choice of filter size depends on the specific application and the desired outcome. A balance must be struck between smoothing and preserving the essential details of the image.

How median filter can be used for noise reduction?

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Median filter is a commonly used non-linear filter for noise reduction in images. It is particularly effective at removing salt-and-pepper noise, which is a type of noise that randomly replaces some pixels with either the maximum or minimum intensity value.

The basic idea behind the median filter is to replace each pixel in the image with the median value of its local neighborhood. The local neighborhood is defined by the size of the filter kernel, which can be chosen based on the amount and type of noise present in the image.

When the median filter is applied to an image, it sorts the pixel values in the local neighborhood and replaces the pixel being processed with the median value. Since the median value is less sensitive to outliers than the mean value, the median filter is particularly effective at removing salt-and-pepper noise, which is characterized by random bright or dark pixels.

Here are the steps involved in using a median filter for noise reduction:

1. Choose the size of the filter kernel: The size of the kernel should be large enough to capture the noise but not too large that it affects the essential details of the image.
2. Move the kernel across the image: The kernel is moved across the image one pixel at a time, and the pixel values within the kernel are sorted.
3. Compute the median value: The median value is the middle value in the sorted list of pixel values. This value is used to replace the pixel being processed.
4. Repeat for all pixels: The above steps are repeated for all pixels in the image, and the resulting image is the filtered image.

In summary, the median filter is a powerful tool for removing salt-and-pepper noise from images. It works by replacing each pixel with the median value of its local neighborhood, which is less sensitive to outliers than the mean value. The size of the filter kernel should be chosen based on the amount and type of noise present in the image.

How image sharpening is performed?

Image sharpening is a technique used to enhance the details and edges in an image. It is usually performed by applying a high-pass filter to the image, which boosts the high-frequency components of the image while suppressing the low-frequency components.

Here are the steps involved in performing image sharpening:

1. Convert the image to grayscale: Image sharpening is usually performed on grayscale images, so if the image is in color, it needs to be converted to grayscale first.
2. Apply a low-pass filter: A low-pass filter is applied to the image to remove high-frequency components, such as noise, from the image. This step is optional but recommended to ensure that the sharpening process does not amplify noise in the image.
3. Subtract the low-pass filtered image from the original image: The resulting image will contain only the high-frequency components, which correspond to the edges and details in the image.
4. Adjust the contrast: The high-pass filtered image will have negative values in some areas. To correct this, the contrast can be adjusted by adding a constant value to the image.
5. Combine the high-pass filtered image with the original image: The high-pass filtered image can be combined with the original image using a blending function, such as the "overlay" blending mode in image editing software. This results in an image that has enhanced details and edges.

There are many variations of the above steps depending on the specific technique used for image sharpening. For example, some techniques use unsharp masking or deconvolution instead of a high-pass filter, while others use different blending modes or different contrast adjustments.

In summary, image sharpening is performed by applying a high-pass filter to the image to enhance the details and edges. This is usually done after applying a low-pass filter to remove noise from the image. The resulting high-pass filtered image is then combined with the original image using a blending function to produce the final sharpened image.

What is unsharp masking, write the steps involved in it

Unsharp masking is an image sharpening technique that enhances the edges and details in an image by accentuating the contrast between adjacent pixels. It is performed by creating a new image that emphasizes the high-frequency components of the original image and then combining it with the original image to produce the final sharpened image.

Here are the steps involved in unsharp masking:

1. Create a blurred image: A blurred version of the original image is created by applying a low-pass filter, such as a Gaussian filter, to the image. This removes the high-frequency components of the image, such as noise and fine details.
2. Subtract the blurred image from the original image: The resulting image is a high-pass filtered version of the original image that contains only the high-frequency components, such as edges and fine details.
3. Scale the high-pass filtered image: The high-pass filtered image is scaled by a factor, usually between 0.2 and 0.7, to control the strength of the sharpening effect.
4. Combine the scaled high-pass filtered image with the original image: The scaled high-pass filtered image is combined with the original image using a blending function, such as the "addition" or "overlay" blending mode in image editing software. This results in an image that has enhanced details and edges.

5. Optional: adjust the contrast: The contrast of the resulting image can be adjusted to make it more visually appealing. This can be done using tools such as the "levels" or "curves" adjustments in image editing software.

Unsharp masking is a powerful technique for image sharpening that can produce high-quality results. However, it is important to use it judiciously, as excessive sharpening can lead to artifacts and an unnatural appearance. It is also important to use appropriate filter settings and scaling factors based on the image content and the desired level of sharpening.

What is high boost filtering?

High boost filtering is a sharpening technique used to enhance the details and edges in an image. It is a variation of the unsharp masking technique, but instead of using a fixed scaling factor to boost the high-frequency components of the image, it allows the user to control the amount of boost using a parameter called the "boost factor."

Here are the steps involved in high boost filtering:

1. Create a blurred image: A blurred version of the original image is created by applying a low-pass filter, such as a Gaussian filter, to the image. This removes the high-frequency components of the image, such as noise and fine details.
2. Create a high-pass filtered image: The original image is subtracted from the blurred image to obtain a high-pass filtered image that contains only the high-frequency components, such as edges and fine details.
3. Apply the high boost filter: The high-pass filtered image is multiplied by a boost factor and added back to the original image. This amplifies the high-frequency components of the image, enhancing the details and edges.

The high boost filter equation can be written as follows:

Sharpened Image = Original Image + (Boost Factor x High-Pass Filtered Image)

where the Boost Factor is a parameter that controls the amount of boost applied to the high-pass filtered image.

The high boost filtering technique is widely used in image processing applications, such as digital photography, video processing, and computer vision. It can produce high-quality sharpening results, but like all image processing techniques, it should be used judiciously and with appropriate parameter settings to avoid artifacts and an unnatural appearance.

What are the different gradient operators?

Gradient operators are used in image processing to detect edges and boundaries in an image. There are several gradient operators that can be used for this purpose, including:

1. Sobel Operator: The Sobel operator is a commonly used gradient operator that uses a 3x3 kernel to calculate the gradient of an image. It computes the gradient in the x and y directions separately, and then combines them to obtain the final gradient magnitude.
2. Prewitt Operator: The Prewitt operator is similar to the Sobel operator, but it uses a 3x3 kernel with slightly different weights to calculate the gradient.

3. Roberts Operator: The Roberts operator is a simple gradient operator that uses a 2x2 kernel to calculate the gradient. It is less computationally expensive than the Sobel and Prewitt operators, but it is also less accurate.
4. Laplacian Operator: The Laplacian operator is a second-order gradient operator that calculates the gradient of the image by computing the sum of the second partial derivatives in the x and y directions. It is more sensitive to noise than the first-order gradient operators.
5. Canny Edge Detector: The Canny edge detector is a multi-stage edge detection algorithm that uses a combination of Gaussian smoothing, gradient calculation, non-maximum suppression, and hysteresis thresholding to produce high-quality edge maps.

These gradient operators have different strengths and weaknesses, and the choice of operator depends on the specific requirements of the application. For example, the Sobel and Prewitt operators are commonly used for real-time applications due to their speed and accuracy, while the Laplacian operator and Canny edge detector are used for more sophisticated applications that require high-quality edge detection.

Explain the Using of first order Derivative for Image Sharpening

First-order derivative operators, such as the Sobel and Prewitt operators, can be used for image sharpening by emphasizing edges and boundaries in an image. The basic idea is to subtract the blurred image from the original image to obtain the high-frequency components, which correspond to the edges and details in the image.

Here are the steps involved in using the first-order derivative for image sharpening:

1. Compute the gradient of the image: The gradient of the image is calculated using a first-order derivative operator, such as the Sobel or Prewitt operator. This operator calculates the first derivative of the image in the x and y directions, which correspond to the horizontal and vertical edges in the image.
2. Obtain the high-frequency components: The blurred image is subtracted from the original image to obtain the high-frequency components, which correspond to the edges and details in the image. This step enhances the edges and boundaries in the image.
3. Add the high-frequency components back to the original image: The high-frequency components are added back to the original image to produce the sharpened image. This step increases the contrast and sharpness of the edges and details in the image.

The formula for image sharpening using the first-order derivative can be written as follows:

Sharpened Image = Original Image - Blurred Image + (Sharpening Factor x Gradient)

where the Sharpening Factor is a parameter that controls the amount of sharpening applied to the image.

Using the first-order derivative for image sharpening is a simple and effective technique, but it can produce some artifacts, such as noise and halos around the edges. To minimize these artifacts, it is important to use an appropriate smoothing filter to obtain the blurred image and to adjust the sharpening factor to achieve the desired amount of sharpening.

Explain Opening and Closing procedure in Morphological Image Processing

Opening and Closing are two fundamental operations in morphological image processing that are used to remove noise and small objects from binary images while preserving the shape and connectivity of the larger objects.

Opening and Closing can be defined as follows:

1. Opening: The opening operation is a combination of erosion followed by dilation. It is used to remove small objects and noise from the foreground (i.e., the white pixels) of a binary image while preserving the larger objects. The operation works by first eroding the image with a structuring element, which reduces the size of the objects and fills in any small gaps between them. Then, the resulting image is dilated with the same structuring element, which restores the size of the larger objects while keeping the small ones removed.
2. Closing: The closing operation is a combination of dilation followed by erosion. It is used to remove small gaps and holes in the foreground of a binary image while preserving the larger objects. The operation works by first dilating the image with a structuring element, which fills in the small gaps and holes in the foreground. Then, the resulting image is eroded with the same structuring element, which restores the shape of the larger objects while keeping the small gaps and holes filled.

The structuring element used in Opening and Closing can have different shapes and sizes, depending on the specific requirements of the application. Commonly used structuring elements include squares, circles, and rectangles, and their size and shape can be adjusted to control the size and shape of the objects that are removed or preserved.

Opening and Closing are useful operations in many image processing applications, such as image segmentation, object detection, and feature extraction. They can be used in combination with other morphological operations to achieve more complex image processing tasks, such as edge detection, boundary extraction, and texture analysis.

Explain Hit and Miss transforms

Hit-and-Miss transform is a morphological operation that is used for binary image processing. It is a type of structuring element operation that can be used to detect specific patterns in binary images, such as edges, corners, and other features. The Hit-and-Miss transform can also be used for image segmentation and feature extraction.

The operation works by using two structuring elements, one called the foreground (F) and the other called the background (B). The F and B structuring elements are designed to detect specific patterns in the image, and their shape and size depend on the desired pattern to be detected. The F structuring element contains the pixels that must match the foreground of the pattern to be detected, while the B structuring element contains the pixels that must match the background of the pattern.

The Hit-and-Miss transform is applied to the binary image by sliding the F and B structuring elements over the image and comparing the pixels in the F and B elements with the corresponding pixels in the image. If the pixels in the F and B elements match the foreground and background of the pattern, respectively, the corresponding pixel in the image is set to 1; otherwise, it is set to 0.

The Hit-and-Miss transform can be used to detect various patterns in the image, such as corners, junctions, T-intersections, and other geometric shapes. The transform can also be used for image segmentation by detecting the boundaries between different regions in the image.

The Hit-and-Miss transform can be expressed mathematically as follows:

$G(x,y) = F(x,y) \cap Cc(B(x,y))$

where $G(x,y)$ is the output image, $F(x,y)$ is the input image, $B(x,y)$ is the background structuring element, $Cc(B(x,y))$ is the complement of the background structuring element, and $\cap$ is the intersection operator.

Overall, the Hit-and-Miss transform is a powerful tool for binary image processing that can be used to detect specific patterns and features in the image, and it is commonly used in many applications such as image recognition, object detection, and segmentation.

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Explain Three Fundamentals steps performed in Edge Detection

Edge detection is an essential technique in image processing that is used to identify and locate the boundaries of objects or regions in an image. There are several edge detection algorithms available, but most of them follow three fundamental steps:

1. Smoothing: In the first step, the input image is smoothed using a filter or kernel to reduce noise and spurious edges. Smoothing the image helps to remove the high-frequency noise and retain the low-frequency edges that are more meaningful. Common smoothing filters used for edge detection include Gaussian filter, median filter, and mean filter.
2. Gradient Calculation: In the second step, the gradient of the smoothed image is calculated. The gradient of an image measures the rate of change of intensity at each pixel location. The gradient provides information about the direction and magnitude of the edges in the image. Common gradient operators used for edge detection include Sobel, Prewitt, and Roberts.
3. Edge Localization: In the third step, the edges in the image are localized and extracted. This is done by thresholding the gradient magnitude image and then applying edge thinning and linking algorithms to connect the edges and eliminate spurious ones. The thresholding operation converts the gradient magnitude image into a binary image where the edges are represented by 1s and the non-edges by 0s. The edge thinning algorithm removes redundant pixels along the edge, and the edge linking algorithm connects the remaining pixels into a contiguous edge.

Overall, the three fundamental steps in edge detection involve smoothing the image to reduce noise, calculating the gradient of the smoothed image to locate the edges, and then localizing and extracting the edges using thresholding, thinning, and linking algorithms. These steps can be performed using various edge detection algorithms, and the choice of algorithm depends on the specific application and requirements.

How are Diagonal edges detected using gradient operators.

Diagonal edges can be detected using gradient operators by using a combination of horizontal and vertical gradient operators. The most commonly used gradient operators for diagonal edge detection are the Sobel and Prewitt operators.

The Sobel operator uses two 3x3 kernels, one for detecting vertical edges and the other for detecting horizontal edges. To detect diagonal edges, we can combine the vertical and horizontal kernels to obtain the diagonal gradient. The diagonal gradient can be computed as follows:

G_d = sqrt((G_x)^2 + (G_y)^2)

where G_d is the diagonal gradient, G_x is the horizontal gradient, and G_y is the vertical gradient. The diagonal gradient represents the magnitude of the edge at each pixel location, and its direction indicates the orientation of the edge.

Similarly, the Prewitt operator uses two 3x3 kernels, one for detecting vertical edges and the other for detecting horizontal edges. To detect diagonal edges, we can also combine the vertical and horizontal kernels to obtain the diagonal gradient. The diagonal gradient can be computed as follows:

G_d = sqrt((G_x)^2 + (G_y)^2)

where G_d is the diagonal gradient, G_x is the horizontal gradient, and G_y is the vertical gradient. The diagonal gradient represents the magnitude of the edge at each pixel location, and its direction indicates the orientation of the edge.

Overall, diagonal edges can be detected using gradient operators by combining the horizontal and vertical gradients to obtain the diagonal gradient. This approach can be used with various gradient operators, and the choice of operator depends on the specific application and requirements.

Explain the steps followed in the Marr-Hildreth edge detector.

The Marr-Hildreth edge detector is a popular edge detection algorithm that uses a Laplacian of Gaussian (LoG) filter to detect edges. The algorithm involves the following steps:

1. Smoothing: The input image is convolved with a Gaussian filter to reduce noise and blur the image. The size of the Gaussian filter depends on the scale of the features to be detected.
2. LoG filter: The smoothed image is then convolved with a Laplacian of Gaussian (LoG) filter to detect edges. The LoG filter is a second-order derivative filter that detects zero-crossings in the image. The size of the LoG filter is also determined by the scale of the features to be detected.
3. Zero-crossing detection: The zero-crossings in the LoG filtered image are detected to locate the edges. A zero-crossing occurs when the pixel intensity changes sign in the filtered image, indicating a change in the image gradient. The zero-crossing points represent the locations of the edges in the image.
4. Thresholding: The zero-crossings are thresholded to eliminate weak and spurious edges. A high threshold is used to retain only strong edges, while a low threshold is used to retain weak edges that are connected to strong edges.
5. Edge localization: The final step involves localizing the edges using edge linking algorithms. This involves connecting the weak edges to the nearby strong edges to form a continuous contour. This step ensures that the edges are accurately localized and that spurious edges are eliminated.

Overall, the Marr-Hildreth edge detector involves smoothing the image with a Gaussian filter, filtering the smoothed image with a LoG filter to detect edges, detecting zero-crossings to locate the edges, thresholding to eliminate weak and spurious edges, and finally, localizing the edges using edge linking algorithms. The algorithm is effective at detecting edges of different scales and orientations and is widely used in computer vision applications.

How local Processing is used for edge linking and boundary detection

Local processing is a common technique used for edge linking and boundary detection in image processing. The technique involves analyzing the pixel values of an image at a local neighborhood around each pixel to determine whether it belongs to an edge or not.

The steps involved in local processing for edge linking and boundary detection are as follows:

1. Gradient calculation: The first step is to compute the gradient of the image using a gradient operator, such as the Sobel or Prewitt operators. The gradient represents the rate of change of pixel intensities, and its magnitude indicates the strength of the edge.
2. Non-maximum suppression: The gradient image is then subjected to non-maximum suppression, which involves suppressing all gradient values except the local maximum along the edge. This step ensures that the edge is detected as a thin line with maximum gradient magnitude.
3. Thresholding: The non-maximum suppressed image is then thresholded to determine which pixels belong to an edge and which do not. Pixels with gradient magnitudes above a certain threshold are considered to be part of an edge.
4. Edge linking: The thresholded image is then subjected to edge linking algorithms, which connect the edge pixels into a continuous curve or contour. The edge linking algorithms use local processing to identify and link pixels that belong to the same edge.
5. Boundary detection: Finally, boundary detection is performed by tracing the contour of the linked edges. This step involves identifying the start and end points of the contour and tracing the curve to detect the boundary of the object in the image.

Overall, local processing is a powerful technique for edge linking and boundary detection, as it enables the detection of complex and irregular shapes in an image. The technique is widely used in computer vision and image processing applications, such as object recognition, segmentation, and tracking.

How Global processing is done using the Hough transform?

The Hough transform is a popular technique for global processing in image analysis and computer vision. It is used for detecting geometric shapes in an image, such as lines, circles, and ellipses. The Hough transform works by mapping the image space into a parameter space, where the parameters of the geometric shapes can be detected and quantified.

The steps involved in global processing using the Hough transform are as follows:

1. Edge detection: The first step is to detect the edges in the image using a suitable edge detection algorithm, such as the Canny edge detector or Sobel operator. The edges represent the boundaries of the geometric shapes to be detected.
2. Parameter space representation: Each edge point in the image is represented as a curve in the parameter space, where the parameters of the geometric shape are detected. For example, for detecting lines, each edge point in the image corresponds to a line in the parameter space defined by the slope and intercept of the line.
3. Accumulator array: The parameter space is represented as an accumulator array, which is a two-dimensional array that accumulates the votes for each parameter of the geometric shape. The accumulator array is initialized to zero and is incremented for each edge point that falls on the curve in the parameter space.
4. Peak detection: The accumulator array is then analyzed to detect the peaks corresponding to the parameters of the geometric shape. The peaks represent the most likely parameters of the geometric shape based on the edge points in the image.

5. Geometric shape detection: Finally, the parameters of the geometric shape are used to detect the shape in the image. For example, for line detection, the parameters are used to determine the endpoints of the line in the image.

Overall, the Hough transform is a powerful technique for global processing in image analysis and computer vision. It can be used to detect geometric shapes in an image with high accuracy, even in the presence of noise and other distortions. The technique is widely used in a range of applications, such as object detection, recognition, and tracking.