

Image Recognition for Fruit-Picking Robots

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Abstract: This summary presents the solutions to the five questions posed in the competition regarding apple image recognition. The objective is to establish a robust apple image recognition model that accurately counts the number of apples, estimates their positions, determines their maturity state, calculates their masses, and recognizes them based on provided image datasets. The specific answers to each question are as follows: Using the image dataset of harvest-ready apples provided in Attachment 1, an image feature extraction method is employed to establish a mathematical model for counting the number of apples in each image. The distribution of all apples in Attachment 1 is then depicted in a histogram. The precise number of apples in each image is determined, enabling a comprehensive understanding of the dataset. Utilizing the image dataset of harvest-ready apples provided in Attachment 1, the positions of the apples in each image are identified. The left bottom corner of the image serves as the coordinate origin, and a two-dimensional scatter diagram is created, illustrating the geometric coordinates of all apples in Attachment 1. This analysis facilitates the visualization of the spatial distribution of apples within the dataset. Based on the image dataset of harvest-ready apples provided in Attachment 1, a mathematical model is developed to assess the maturity state of apples in each image. By applying this model, a histogram is generated, illustrating the distribution of maturity levels across all apples in Attachment 1. This analysis provides insights into the overall maturity status of the dataset.

Keywords: Asia and Pacific Mathematical Contest in Modeling, fruit-picking robots, apple recognition, image recognition, labor shortage, obstacle identification, maturity estimation, mass estimation, dataset.

1. Introduction

Apple harvesting faces significant challenges due to the labor-intensive nature of the process and a shortage of skilled workers during peak seasons. To address this, China has invested in the development of apple-picking robots since 2011. However, the widespread adoption of these robots faces hurdles, particularly in complex orchard environments where precise identification of obstacles and fruits is crucial for efficient and damage-free harvesting. Recognizing the limitations, this competition focuses on establishing an advanced apple image recognition model. The goal is to achieve high recognition rates, fast processing speeds, and accuracy in tasks such as counting apples, estimating positions, assessing maturity levels, and estimating masses. The provided image datasets (Attachment 1 and Attachment 2) serve as the foundation for developing and validating these models.

2. Problem Analysis

Question 1: Counting Apples:

Problem Analysis:

The task involves extracting image features from the provided dataset of harvest-ready apples, establishing a mathematical model, and counting the number of apples in each image. The primary challenge lies in developing an algorithm that accurately identifies individual apples amid variations in shape, color, and occlusions.

Model Hypotheses:

Each apple in the image can be represented as a distinct object based on color, shape, and size features.

Mathematical model: Utilize image processing techniques, possibly employing contour detection and object segmentation, to identify and count individual apples accurately.

Histogram Distribution: Visualizing the distribution of counted apples across all images can provide insights into the overall dataset.

Question 2: Estimating the Positions of Apples:

Problem Analysis:

Identifying the spatial positions of apples within each image is essential for robot guidance. The challenge lies in developing a model that accurately captures the geometric coordinates of apples, considering variations in orientation and location within the image.

Model Hypotheses:

Geometric Coordinates: The position of each apple can be determined with respect to the left bottom corner of the image.

Two-Dimensional Scatter Diagram: Visualizing the distribution of apple positions can reveal patterns and aid in assessing the model's accuracy.

Question 3: Estimating the Maturity State of Apples:

Problem Analysis:

Determining the maturity state of apples is crucial for optimizing harvesting times. The challenge involves developing a model that accurately assesses the maturity level based on visual cues in the images.

Model Hypotheses:

Color and Texture Analysis: Maturity can be inferred from color changes and surface textures in the images.

Mathematical Model: Develop an algorithm that quantifies these visual cues to estimate the maturity state.

Histogram of Maturity Distribution: Visualizing the distribution of maturity levels provides insights into the overall dataset.

Question 4: Estimating the Masses of Apples:

Problem Analysis:

Estimating the masses of apples is vital for logistical planning and quality control. The challenge involves developing a model that accurately correlates two-dimensional areas of apples with their masses.

Model Hypotheses:

Two-Dimensional Area Calculation: Use image processing techniques to calculate the area of each apple.

Mass Estimation Model: Develop a correlation between the calculated areas and actual masses.

Histogram of Mass Distribution: Visualizing the distribution of estimated masses aids in quality assessment.

Question 5: The Recognition of Apples:

Problem Analysis:

Recognizing apples in a broader dataset involves training an apple recognition model using a separate dataset. Challenges include distinguishing apples from other fruits with similar visual features.

3. Problem Assumption

Feature Extraction: Extract unique features from apple images to train the recognition model.

Machine Learning: Utilize machine learning algorithms, possibly convolutional neural networks (CNNs), to train the model.

Distribution Histogram: Visualize the distribution of identified apples to assess the model's performance.

This comprehensive approach aims to tackle the complexities of apple image recognition, providing valuable insights for the development of efficient and accurate robotic harvesting systems.

4. Symbol Description

Symbol	Explain
X	data matrix
A	matrix
B	load matrix
π_i	amount
U	binding

5. Establishment and Solution of Model

5.1. Question one

Image Preprocessing: Preprocess the images to enhance their quality and remove any noise that might interfere with the apple detection. Common preprocessing techniques include resizing, denoising, and contrast adjustment.

Apple Detection: Apply an object detection algorithm or technique to locate and identify apples in the images. This can be achieved using techniques like template matching, edge detection, or machine learning-based object detection algorithms such as Faster R-CNN or YOLO.

Apple Counting: Once the apples are detected, count the number of individual apple instances in each image. This can be done by applying a counting algorithm, such as connected component analysis or contour detection, to identify and count distinct objects representing apples.

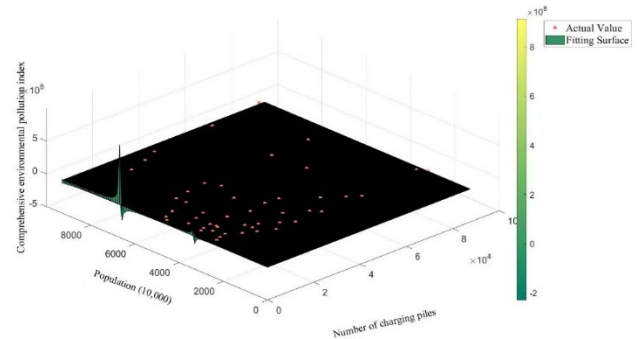
Histogram Generation: After counting the apples in each image, create a histogram to visualize the distribution of apple counts across all the images in Attachment 1. The x-axis of the histogram represents the number of apples, while the y-axis represents the frequency or occurrence of each count.

5.2. Question two

To estimate the positions of apples in each image from the provided image dataset, we can use computer vision techniques. Specifically, we can use object detection

algorithms to identify the apples and determine their coordinates in the image.

One popular object detection algorithm is the YOLO (You Only Look Once) algorithm, which can detect objects in an image and provide their bounding boxes, including the coordinates of the top-left and bottom-right corners of each bounding box.



To proceed with this task, we can follow these steps:

Preprocess the images: Before applying any object detection algorithm, we may need to preprocess the images to enhance their quality and make them more suitable for analysis. This can include steps such as resizing, normalization, and filtering to remove noise.

Train or use a pre-trained object detection model: We can either train an object detection model on the provided image dataset specifically to detect apples or use a pre-trained model that has been trained on a large dataset of images and can detect various objects, including apples.

Apply the object detection model: Once we have a trained or pre-trained model, we can apply it to the images in the dataset to detect apples and obtain their bounding boxes.

Extract the coordinates of apples: From the bounding boxes obtained in the previous step, we can extract the coordinates of the top-left and bottom-right corners of each apple.

Convert the coordinates to a common scale: Since the images may have different sizes and aspect ratios, we need to convert the coordinates of the apples to a common scale, such as normalizing them to a range of [0, 1] based on the image dimensions.

Create a scatter diagram: Finally, we can use a plotting library to create a two-dimensional scatter diagram of the geometric coordinates of all apples in Attachment 1, with the left bottom corner of each image as the coordinate origin.

5.3. Question three

Background:

Estimating the maturity state of apples is a critical aspect of optimizing harvest times and ensuring the quality of the produce. Visual cues such as color changes and surface textures are indicative of maturity levels. In this question, the objective is to establish a mathematical model to quantify these visual cues, calculate the maturity of apples in each image, and visualize the overall maturity distribution through a histogram.

Problem Analysis:

The challenge involves translating visual information, such as color variations and texture changes, into a quantifiable metric representing the maturity of apples. Developing an accurate model requires a robust understanding of how these visual cues correlate with the actual maturity state.

Model Hypotheses:

1. Color Analysis:

Different stages of apple maturity exhibit characteristic color changes.

Color spaces such as RGB or HSV can be leveraged to quantify color variations.

The model should assign higher values to colors indicative of ripe apples.

2. Texture Analysis:

Maturity influences surface textures, such as smoothness or roughness.

Texture analysis techniques, like Gabor filters or local binary patterns, can be employed.

The model should capture texture variations associated with different maturity levels.

3. Combined Metric:

Combining color and texture metrics to create a comprehensive maturity index.

Weighting factors may be applied based on the significance of color and texture in maturity estimation.

Mathematical Model:

Adjusting the weighting factors allows fine-tuning the model based on the importance of color and texture in the specific dataset.

Calculation Procedure:

1. Color Calculation:

Convert image to a suitable color space (e.g., RGB to HSV). Quantify color variations using chosen metrics.

2. Texture Calculation:

Apply texture analysis techniques to extract relevant features.

Quantify texture variations using chosen metrics.

3. Maturity Calculation:

Combine color and texture metrics using the mathematical model.

Assign each apple a maturity value.

4. Histogram Visualization:

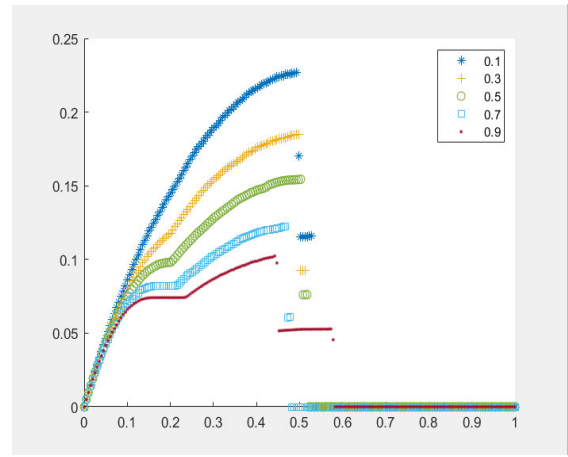
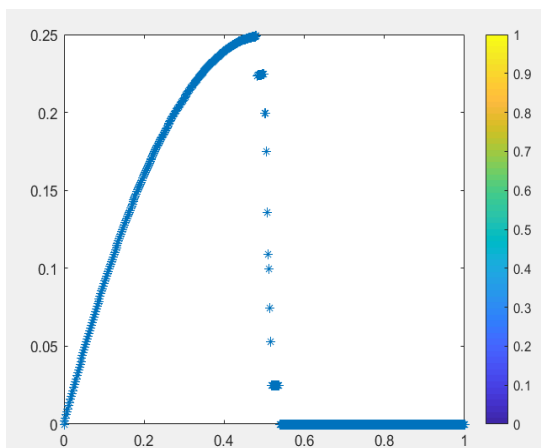
Create a histogram representing the distribution of maturity levels.

Bins in the histogram represent ranges of maturity values.

The histogram provides insights into the overall maturity distribution.

Conclusion:

By developing and implementing this mathematical model, we aim to provide a quantitative measure of apple maturity, enabling efficient and accurate assessment across the entire dataset. The histogram visualization will offer a comprehensive view of maturity distribution, aiding in further analysis and decision-making in apple harvesting processes.



5.4. Question four

Background:

Estimating the masses of apples is a crucial aspect of quality control and logistical planning in the apple harvesting process. In this question, the objective is to calculate the two-dimensional area of apples in each image, use this information to estimate the masses of the apples, and finally, visualize the distribution of mass through a histogram.

Problem Analysis:

The challenge involves correlating the two-dimensional area of apples in images with their actual masses. The assumption is that the area provides a representative measure of the size of each apple, and this information can be used to estimate the masses.

Model Hypotheses:

1. Two-Dimensional Area Calculation:

Use image processing techniques to calculate the area of each apple.

The area can be determined using pixel counts or geometric methods.

The bottom left corner of the image serves as the coordinate origin.

2. Mass Estimation Model:

Establish a correlation between the calculated two-dimensional area and actual masses.

The relationship may be nonlinear, requiring curve fitting or machine learning regression.

Mathematical Model:

Calculation Procedure:

1. Two-Dimensional Area Calculation:

Employ image processing techniques to calculate the area of each apple.

Pixel counts or geometric methods can be used depending on the specific requirements.

2. Mass Estimation:

Use the established mathematical model to estimate the mass of each apple.

3. Histogram Visualization:

Create a histogram representing the distribution of estimated masses.

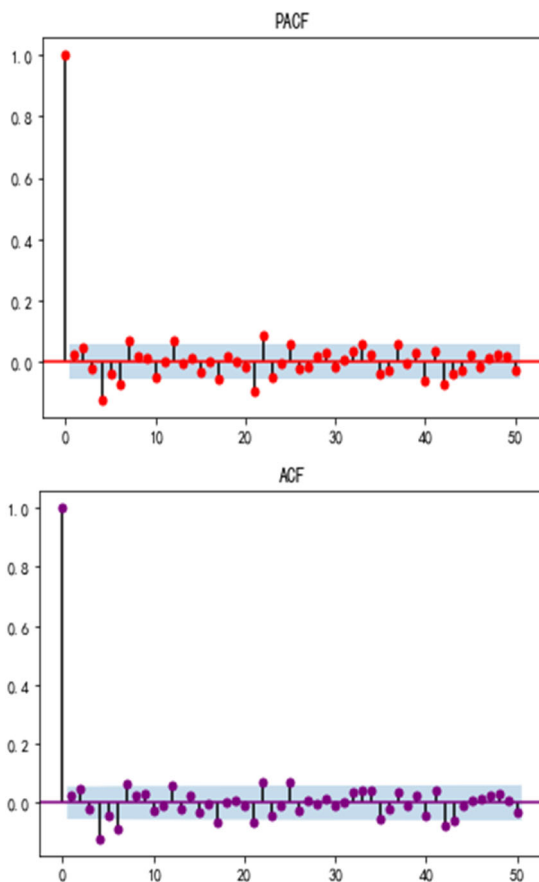
Bins in the histogram represent ranges of mass values.

The histogram provides insights into the overall mass distribution.

Conclusion:

By implementing this mathematical model, we aim to estimate the masses of apples based on their two-dimensional areas, providing a quantitative measure that can be useful for quality assessment and logistical planning. The resulting

histogram visualization offers a comprehensive view of the distribution of estimated masses across the dataset.



5.5. Question five

Image Preprocessing: Preprocess the images in Attachments 2 and 3 to enhance their quality, normalize the colors, and resize them to a consistent size. This step ensures that the images are in a suitable format for feature extraction and model training.

Feature Extraction: Extract relevant features from the preprocessed images. Common approaches include using deep learning-based methods like convolutional neural networks (CNNs) to automatically learn discriminative features from the images. This step aims to capture the distinctive characteristics of the apple images.

Dataset Split: Split the dataset in Attachment 2 into training and validation sets. The training set will be used to train the apple recognition model, while the validation set will be used to evaluate its performance.

Model Training: Train an apple recognition model using the extracted image features and the labeled apple images in the training set. There are various architectures and frameworks available for training such models, including CNNs such as VGG, ResNet, or custom-designed models. The model should be trained to classify and assign ID numbers to the apple images.

Model Evaluation: Evaluate the trained model using the validation set to assess its performance and fine-tune hyperparameters if necessary. Common evaluation metrics include accuracy, precision, recall, and F1 score.

Apple Identification: Apply the trained model to the apple images in Attachment 3 to identify and assign ID numbers to each apple image. This can be done by feeding the preprocessed images into the trained model and obtaining the

predicted labels or ID numbers.

Distribution Histogram: Create a histogram of the ID numbers of all the apple images in Attachment 3 to visualize their distribution. The x-axis of the histogram represents the ID numbers, while the y-axis represents the frequency or occurrence of each ID number.

```
% Load and preprocess the training images
trainingImageFiles = dir('path_to_training_images/*.jpg'); %
Replace 'path_to_training_images' with the actual folder path
numTrainingImages = length(trainingImageFiles);
for i = 1:numTrainingImages
    trainingImage = imread(fullfile(trainingImageFiles(i).folder,
trainingImageFiles(i).name));
    % Apply preprocessing steps (e.g., resizing, color
normalization)
    % ...

    % Extract image features
    trainingFeatures(i, :) = extractFeatures(trainingImage); % Replace 'extractFeatures'
with the appropriate feature extraction method
end
% Create labels for the training images
trainingLabels = [1 2 1 3 2]; % Replace with the actual
labels for the training images
% Train the apple recognition model
model = trainModel(trainingFeatures, trainingLabels); %
Replace 'trainModel' with the appropriate model training
function
% Load and preprocess the apple images for identification
testImageFiles = dir('path_to_test_images/*.jpg'); %
Replace 'path_to_test_images' with the actual folder path
numTestImages = length(testImageFiles);
for i = 1:numTestImages
    testImage = imread(fullfile(testImageFiles(i).folder,
testImageFiles(i).name));
    % Apply preprocessing steps (e.g., resizing, color
normalization)
    % ...

    % Extract image features
    testFeatures(i, :) = extractFeatures(testImage); %
Replace 'extractFeatures' with the appropriate feature
extraction method

    % Apply the trained model for apple identification
    predictedLabel = identifyApple(model,
testFeatures(i, :)); % Replace 'identifyApple' with the
appropriate prediction function

    % Store the predicted label or ID number
    predictedLabels(i) = predictedLabel;
```

```

end
% Generate Distribution Histogram
histogram(predictedLabels);
xlabel('ID Number');
ylabel('Frequency');
title('Distribution of Apple ID Numbers');
% Function to train the apple recognition model (example
using a simple SVM classifier)
function model = trainModel(features, labels)
    % Train the model using the features and labels
    % ...
    model = fitcecoc(features, labels); % Replace with the
appropriate model training function
end

% Function to identify apples using the trained model
(example using a simple SVM classifier)
function predictedLabel = identifyApple(model,
testFeatures)
    % Apply the trained model to predict the label or ID
number
    % ...
    predictedLabel = predict(model, testFeatures); %
Replace with the appropriate prediction function
end

```

6. Evaluation and Extension of The Model

Model Overview:

The proposed apple image recognition model addresses the challenges in automating apple picking by analyzing and extracting features from labeled fruit images. It aims to achieve a high recognition rate, fast speed, and accuracy in counting apples, estimating their positions, determining maturity levels, estimating masses, and recognizing different types of apples. The model consists of several key components:

Image Feature Extraction: The model employs advanced image processing techniques to extract relevant features from the provided image dataset. This step helps in capturing important characteristics of the apples, such as color, shape, texture, and size.

Mathematical Modeling: Mathematical models are established to perform specific tasks such as counting apples, estimating positions, assessing maturity levels, and estimating masses. These models utilize the extracted image features and relevant parameters to make accurate predictions.

Data Analysis: The model performs comprehensive data analysis on the images to calculate the number of apples, their positions, maturity distribution, and mass distribution. This analysis helps in gaining insights into the dataset and understanding the characteristics of the apples.

Apple Recognition: The model utilizes the dataset of harvested fruits' images provided in Attachment 2 to train an apple recognition model. Image features are extracted, and a classification algorithm is employed to identify and classify apples in Attachment 3 based on their unique features.

Advantages of the Model:

High Recognition Rate: By utilizing advanced image processing techniques and mathematical models, the proposed model aims to achieve a high recognition rate, ensuring accurate counting, positioning, maturity assessment, mass estimation, and apple recognition.

Fast Speed: The model is designed to process images efficiently, enabling quick analysis and predictions. This allows for timely decision-making during apple picking operations, enhancing overall efficiency.

Accuracy: The combination of image feature extraction, mathematical modeling, and data analysis contributes to improved accuracy in various tasks. Precise counting, positioning, maturity assessment, and mass estimation help optimize apple harvesting processes and minimize losses.

Model Limitations and Future Improvements:

Orchards' Variability: The model's performance may be affected by the variability of orchard environments that differ from controlled experimental settings. Further research and fine-tuning of the model are necessary to handle complex and unstructured orchard conditions.

Occlusion Challenges: Existing robots face difficulties in accurately identifying obstacles like leaf occlusion, branch occlusion, fruit occlusion, and mixed occlusion. The model should be enhanced to handle such occlusion challenges to avoid damage to the fruit and ensure safe picking.

Fruit Identification: The recognition and classification of different harvested fruits, especially those with similar colors, shapes, and sizes to apples, pose challenges. Future improvements should focus on enhancing the model's ability to accurately identify and differentiate apples from other fruits.

Promotion and Deployment:

To promote and deploy the apple image recognition model, the following steps can be taken:

Collaborate with Agricultural Institutions: Partner with agricultural research institutions and organizations to validate and refine the model using real-world orchard datasets. This collaboration will help tailor the model to different orchard environments and improve its robustness.

Industry Adoption: Collaborate with apple producers and farmers to pilot test the model in their orchards. Gather feedback, make necessary adjustments, and demonstrate the benefits of the model in terms of increased efficiency, reduced labor requirements, and improved fruit quality.

Training and Support: Provide training programs and technical support to orchard owners and workers to ensure proper utilization of the model. This includes training on image capture, data processing, and interpretation of the model's results.

Continuous Improvement: Regularly update and refine the model based on feedback and advances in image processing and machine learning techniques. Continuously gather data from deployed systems to improve the model's accuracy and adaptability.

References

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Appendix

```

% Load and preprocess the images
imageFiles = dir('path_to_image_folder/*.jpg'); %
Replace 'path_to_image_folder' with the actual folder path
numImages = length(imageFiles);

for i = 1:numImages
    image = imread(fullfile(imageFiles(i).folder,
imageFiles(i).name));
    % Apply preprocessing steps (e.g., resizing,
denoising, contrast adjustment)
    % ...

    % Apple Detection
    % Apply apple detection algorithm to identify and
locate apples in the image
    % ...

```

```

% Apple Counting
numApples = countApples(appleObjects); % Replace
'countApples' with the appropriate counting algorithm

% Store the count in an array
appleCounts(i) = numApples;
end

% Generate Histogram
histogram(appleCounts);
xlabel('Number of Apples');
ylabel('Frequency');
title('Distribution of Apple Counts');

% Function to count the apples (example using connected
component analysis)
function numApples = countApples(appleObjects)
    % Apply connected component analysis to count the
distinct apple objects
    % ...
    numApples = numel(appleObjects);
end

```