Review

Research Progress on Non-destructive Detection of Fruits Based on Infrared Thermal Imaging

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Abstract: Approximately one-third of fruits worldwide are lost or wasted during postharvest circulation, and non-destructive testing technologies play a vital role in mitigating such postharvest fruit losses. Featuring broad versatility, high detection efficiency and absence of ionizing radiation, infrared thermal imaging has become a key technical approach for non-destructive fruit inspection. This paper systematically reviews signal processing strategies and intelligent identification modeling algorithms for infrared thermal imaging based fruit quality testing in recent years. It elaborates the fundamental principles and practical performance of combining infrared thermograms with temperature difference thresholding, image processing, frequency domain analysis, conventional machine learning, and deep learning algorithms. Numerous studies have verified the capability of infrared thermal imaging to detect mechanical bruises, ripeness levels, pathological deterioration, pest infestation, and subsurface damage depth in fruits. Furthermore, this technique solves long-standing challenges in the non-destructive detection of dark-hued fruits. With continuous scientific research and technical improvements, infrared thermal imaging will further support smart agriculture and promote the fruit production processing industry toward intellectualization, higher efficiency, and large-scale deployment.

Keywords: Infrared thermal imaging; Non-destructive detection; Fruit detection; Image processing; Deep learning

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1. Introduction

Fruits occupy an important position in human dietary structures [1]. After fresh fruits suffer combined static and dynamic external forces including impact, friction, extrusion and puncture, their quality degrades and shelf-life shortens, which further leading to sorting elimination [2]. Approximately one-third of fruits around the world suffer losses and waste in post-harvest links, which not only pushes up market prices and reduces growers' income, but also increases resource pressure on food processing and logistics [3].

In recent years, numerous researchers worldwide have continuously carried out research on non-destructive detection technologies for identifying various fruit damages and evaluating quality to reduce post-harvest losses. Infrared thermal imaging is a non-destructive, rapid real-time monitoring method, which can accurately detect object surface temperature and reflect internal invisible damage, and is not limited by fruit colour [4,5]. In the research on fruit maturity, it is found that the temperatures of guava, avocado, kiwifruit, peach and banana rise continuously with the increase of maturity [6,7]. In terms of pathological and pest damage detection, infrared detection can successfully identify kiwifruit soft rot, apple watercore, mango infested by Bactrocera dorsalis and mouldy peach, and can judge the severity of fruit mildew [8,11]. In the field of mechanical damage detection, studies on apples, tomatoes, guavas and Chinese jujubes show that there are obvious temperature differences between bruised fruit surfaces and intact surfaces [12-16]. Other studies indicate that different defect types such as apple bruises and rot have distinctive temperature-difference characteristics [17]. However, infrared thermal imaging technology faces many challenges in practical application, including operation convenience, real-time data performance and maintenance of fruit freshness, These drawbacks constitute major bottlenecks for practical deployment and indicate important directions for future research and development.

Most previous reviews summarise various pre-harvest and post-harvest application scenarios of infrared thermal imaging for fruits and vegetables and emphasise its wide applicability. This paper mainly sorts out the automatic identification and modelling methods in infrared-thermal-imaging-based fruit detection. According to algorithm principles, current studies are classified into image-processing methods, frequency-domain analysis methods, traditional machine-learning methods and deep-learning methods. The advantages and disadvantages of different methods in fruit non-destructive detection are reviewed, and development trends are put forward, so as to provide references for further relevant research.

2. Infrared Thermal Imaging System for Fruit Non-Destructive Detection

An infrared thermal imaging system consists of an infrared detector, a signal-processing unit and an image-acquisition unit. The infrared energy emitted by objects is absorbed by the detector and converted into electric pulses, which are converted into thermal images by the signal-processing unit [2]. Figure 1 shows the basic components of a thermal-imaging system for non-destructive fruit inspection.

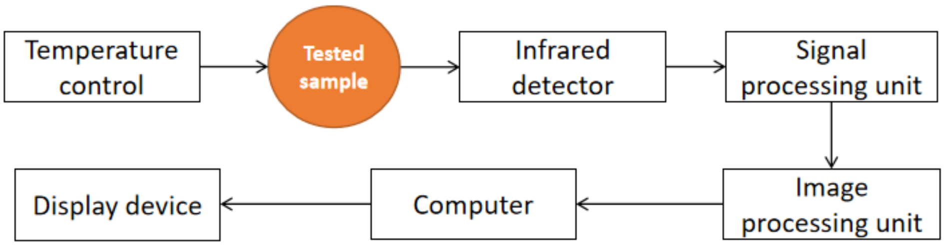

Figure 1. Basic Composition of the Infrared Thermal-imaging System for Fruit Non-Destructive Detection.

According to whether an external heating source is used in the detection process, thermal imaging can be divided into passive thermography and active thermography. Passive thermography detects samples without external thermal excitation, and obtains relative temperature distribution with the temperature of similar targets or ambient reference as benchmark. Active thermography applies external thermal excitation to measured objects. The thermal properties of measured materials will significantly affect the heat-transfer process, thus forming surface temperature differences in regions with different thermophysical properties [18].

The information contained in infrared thermograms is complex. Environmental interference factors and the stability of sample status must be comprehensively considered to ensure measurement accuracy [19]. Excessively long heating time will reduce the temperature difference between diseased and healthy tissues [9]. For active infrared-thermal-imaging-based fruit detection, it is necessary to regulate appropriate heat-source power, heating duration, relative distance and angle between heat source and fruits, as well as image-capturing time [20]. Conveyor-belt speed should also be adjusted if real-time detection is to be realised [21].

For active thermography detection, multiple temperature-control schemes adapted to fruit physiological characteristics have been developed. Zhou et al. heated apple samples for 30-40 s and then stopped heating to continuously capture infrared images, focusing on the cooling stage from 29 C to 24 C [17]. Hou et al. heated apple samples for 50 s to record infrared videos, then turned off the heater and started the heat-dissipation device to record videos for another 50 s [22]. In the detection of apple watercore, Baranowski et al. transferred apples from cold storage at 1.5 C to a constant-temperature detection area of 20 C, and started formal measurement when the fruit surface temperature rose to about 7.5 C [9]. Lin et al. proposed a cold-excitation mode: fruits were transferred from room temperature to a low-temperature environment and imaged after cooling stabilisation [23]. El-Ramady et al. also confirmed that there were differences in temperature changes between bruised tissues and healthy tissues within several hours after cold excitation [24]. Rapid cooling of fruits from room temperature to refrigeration temperature is feasible in the fruit supply chain and conforms to the existing storage process; therefore cold-excitation thermography is also a promising solution.

3. Algorithms for Fruit Non-Destructive Detection Using Infrared Thermal Imaging

3.1. Image Processing Methods

The main infrared image-processing algorithms applied to fruit detection include edge-detection method, K-means clustering and Grey-Level Co-occurrence Matrix (GLCM).

For the edge-detection method, pre-processing operations such as contrast stretching and histogram equalisation are performed on infrared thermograms firstly. Then morphological operations including median-filter denoising, dilation, hole filling, maximum connected-region searching and edge detection are carried out to obtain the contours of fruits and damaged areas. Satone et al. adopted the edge-detection method for apple damage detection and achieved an overall accuracy of 94%, while the overall accuracy of detection based on visible-light images was 56.66% [25]. Sofia Jennifer et al. collected thermal images of five types of experimental objects including intact fruits, mechanically bruised and rotten fruits: apples, bananas, guavas, sapodillas and tomatoes [26]. The edge-detection method achieved an average bruise-detection accuracy of 92.458%.

K-means clustering realises automatic image segmentation by clustering pixels with similar greyscale values. Yogesh et al. adopted segmentation technologies including Speeded-Up Robust Features (SURF), Otsu's thresholding, K-means and watershed, combined with texture analysis to process thermal images for apple defect detection [27]. Jebita et al. combined K-means with Lab colour space (L: lightness, a: red-green channel, b: yellow-blue channel) analysis, which can effectively identify and segment bruised regions in thermal images of apples, pomegranates and guavas [28]. Roy et al. performed anisotropic diffusion and K-means clustering segmentation on apple thermal images to extract bruised regions [29]. Four evaluation indicators were used to objectively quantify and verify the segmentation results. The Probabilistic Rand Index (PRI) reached 0.8827; Variation of Information (VoI), Global Consistency Error (GCE) and Boundary Displacement Error (BDE) were 0.0003, 0.1192 and 0.0397 respectively, indicating that the segmentation results were highly consistent with manually annotated ground-truth images.

The GLCM method firstly calculates the grey-level co-occurrence matrix of infrared images, and then extracts image texture features such as energy, dissimilarity, contrast, homogeneity and entropy from the matrix. Fruit quality is judged according to whether the feature values exceed statistical thresholds. GLCM features quantify the greyscale distribution regularity, texture depth, local mutation and continuity of infrared thermograms. Kale et al. extracted five core GLCM features including contrast, dissimilarity, homogeneity, energy and correlation from pomegranate thermal images, and calculated the mean, variance and standard deviation of thermal-image greyscale values [30]. The results showed that the mean value, contrast and dissimilarity of intact fruits were lower than those of damaged fruits. Roy et al. also adopted the GLCM method for infrared image processing and extracted five features: contrast, homogeneity, energy, entropy and correlation [29]. The results indicated that homogeneity and correlation could effectively distinguish intact apples from bruised apples. The fractal dimension calculated by the box-counting method was less than 1.25 for intact apples and greater than 1.25 for bruised apples. This is because the internal structure of bruised apples is disordered and component heterogeneity is stronger, leading to higher fractal-dimension values.

3.2. Frequency Domain Analysis Methods

In active infrared-thermal-imaging-based fruit detection, Frequency domain analysis algorithms adjust the power of heat sources in different periods to make sample temperature change with time. Fast Fourier Transform (FFT) is performed on the temperature time-series signal of a single pixel to obtain frequency-domain and phase information as object features (Figure 2). The main frequency-domain-analysis methods used for fruit detection include lock-in thermography (LIT), pulsed-phase thermography (PPT) and frequency-modulated thermal-wave imaging (FMTWI).

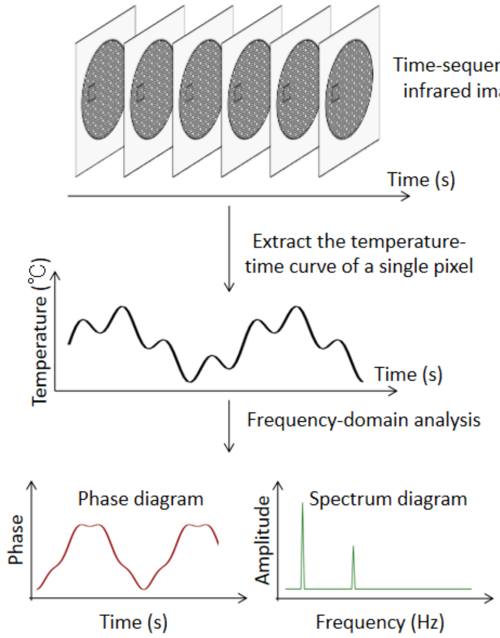

Figure 2. Schematic Diagram of the Frequency-Domain Analysis Method.

The heat source of infrared lock-in thermography generates periodic sinusoidal thermal waves (Figure 3a). Thermal waves propagate into the sample and reflect at subsurface defects. The reflected thermal waves change the surface temperature modulation state of the sample and further form oscillating interference thermal waves [31]. Kim et al. carried out pear research using LIT technology [31]. Under the frequency of 0.1 Hz, the size and position of early bruises could be clearly detected in the phase diagram of damaged pears, and the damage degree showed a good linear relationship with phase difference.

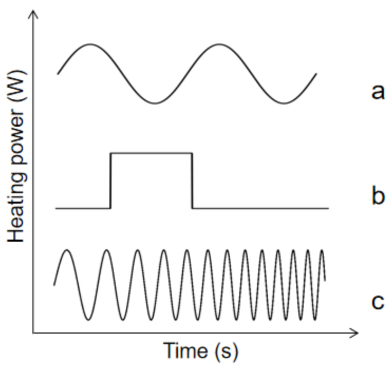

Figure 3. Thermal Excitation Waveforms Used in Frequency-domain Analysis. (A) Lock-in Thermography; (B) Pulsed-phase Thermography; (C) Frequency-modulated Thermal-wave Imaging

Pulsed-phase thermography applies independent thermal pulses to samples (Figure 3b) [32]. Baranowski et al. collected PPT thermal-image sequences of three apple cultivars (Gloster, Jonagold, Champion) [33]. The results showed that bruise depth had a significant linear correlation with phase features, with correlation coefficients of 0.98, 0.96 and 0.96 for Gloster, Jonagold and Champion respectively. It demonstrates that the PPT method can detect early subsurface bruises at millimetre scale in fruits. Wang et al. extracted amplitude-spectrum and phase-spectrum features of apples using the PPT method, followed by principal-component analysis, total-harmonic-distortion calculation, iterative threshold segmentation, Otsu segmentation and morphology-based automatic defect-edge recognition, so as to extract clear and complete defect edges [34].

Frequency-modulated thermal-wave imaging technology adopts linearly-modulated sinusoidal heat sources (Figure 3c). Such continuous frequency sweeping allows thermal waves to penetrate the sample, and the penetration depth is determined by the thermal diffusivity and geometric shape of materials [35]. Bharadwaj et al. adopted FMTWI to detect hidden rotten areas in apples and oranges, and proposed post-processing methods including frequency-domain phase (FDP), time-domain phase (TDP) and cross-correlation coefficient (CCC) [35]. The results showed that CCC, with matched-filter characteristics, achieved better rotten-tissue detection performance and could stably distinguish healthy and rotten regions.

3.3. Traditional Machine Learning Methods

In fruit infrared detection research, traditional machine-learning methods rely on manual feature engineering to extract features such as temperature, image-processing features and spectral features from raw infrared data. The screened features are input into machine-learning models for training to realise classification and discrimination of fruit quality [36].

In machine-learning methods using temperature features, Zhang et al. adopted a one-dimensional Fisher discriminant model to distinguish kiwifruit samples (pricked + soft-rot-infected, merely pricked, healthy), with an accuracy of 94.3% [8]. Hou et al. extracted statistical features of temperature difference between healthy and defective regions of apples and combined them with Support Vector Machine (SVM), achieving a classification accuracy of 93.7% [22]. This method can effectively identify invisible fungal infection and epidermal scratches of apples, and is also applicable to the detection of other invisible defects such as bruises and frost damage. Zolfagharnassab et al. carried out maturity grading research (immature, mature, over-mature) of oil-palm fruit bunches [37]. Taking the temperature difference between average fruit-bunch temperature and ambient temperature as features, classification models including Linear Discriminant Analysis (LDA), Mahalanobis discriminant analysis, Artificial Neural Network (ANN) and Kernel K-Nearest-Neighbour (KNN) were adopted. Among them, ANN obtained the optimal classification performance with the highest accuracy of 92.5%.

In terms of the application of image-processing features, Das et al. adopted an encoder-decoder-based segmentation method to accurately segment bruised regions from complete infrared images [38]. Morphological features were extracted from bruised regions, and classical machine-learning classifiers were used to classify apple bruise severity into three grades: slight, moderate and severe. The average accuracy, specificity and sensitivity reached 90.96%, 91.37% and 90.71% respectively. Haq et al. input five categories of features including thermal-image colour, shape, texture, gradient and statistical features into an Adaptive-Neuro-Fuzzy-Inference-System model for apple grading into five levels: excellent, good, medium, poor and very poor, with an overall accuracy of 97.21% [39]. Jawale et al. extracted GLCM features from apple thermal images to train ANN models, which could successfully distinguish bruised apples from intact ones [40].

For spectral-feature-based applications, Kuzy et al. combined time-domain and frequency-domain infrared features of blueberries and adopted multivariate algorithms including LDA, SVM, K-Nearest-Neighbour, logistic regression and random forest for classification. The recognition accuracies of bruised and healthy fruits reached 88% and 79% for Farthing and Meadowlark blueberry cultivars respectively [32].

3.4. Deep Learning Methods

Deep neural networks break the multi-stage processing paradigm combining manual feature engineering and shallow classifiers, and gradually form end-to-end task modes. Raw images are directly fed into the input terminal, and hidden layers adaptively aggregate and select features to autonomously learn features from pixel-level information and complete target inference [36]. Das et al. compared temperature features, greyscale-intensity features, texture features, shape features and deep-convolutional-neural-network features in apple bruise detection, and the results showed that features derived from deep convolutional neural networks achieved the best discrimination performance [41].

Image classification accounts for most deep-learning applications in fruit infrared-thermal-image analysis. Low et al. divided white-fleshed guava samples into three categories: unripe, ripe and overripe [42]. Five deep-learning models including AlexNet, Inception-v3, GoogLeNet, ResNet-50 and VGGNet-16 were systematically evaluated and compared. VGGNet-16 achieved optimal performance, with average precision of 0.92, sensitivity of 0.93, specificity of 0.96, F1-score of 0.92 and accuracy of 0.92. Melesse et al. designed a lightweight Convolutional Neural Network (CNN) suitable for thermal images, which can be directly deployed on Central Processing Unit (CPU). Four-class classification of bananas (fresh, ripe, overripe, rotten) achieved an average accuracy of 0.98 [43]. Raviteja et al. constructed a composite classification model combining SVM and MobileNet [44]. The optimal accuracy reached 93% in maturity classification, shelf-life prediction and bruise-detection tasks. After hyper-parameter adjustment of DenseNet, Dong et al. achieved the optimal classification accuracy of 99.5% for distinguishing intact and bruised Chinese jujubes [16]. Pugazhendi et al. built a modified CNN model with two activation functions for thermal-image-based mango classification of damaged and intact fruits, obtaining a classification accuracy of 99.6% [45]. Optimised CNN models were used for bruise classification of strawberry thermal images by Dong et al., yielding weighted average precision of 0.98, recall of 0.98, F1-score of 0.98 and accuracy of 0.98 [16]. Zeng et al. adopted the classic LeNet model for pear bruise classification, and the best test-set accuracy reached 99.25% [46].

At present, there are relatively few studies on deep-learning-based image segmentation for fruit infrared thermograms. Due to the generally blurred boundaries and low contrast of infrared images, conventional models still have obvious defects in extracting bruised regions. Das et al. proposed a novel multi-scale encoder-decoder network architecture with a bruise-region attention module to realise self-attention mechanism, which can effectively extract bruised regions of apples [47]. Experiments on the TU-IR apple infrared image dataset obtained a Dice Similarity Coefficient (DSC) of 0.8990 and an F-measure of 0.8911 [41].

Lin et al. carried out research on object detection for apple infrared thermal images using the YOLOv5s model [23]. Although this algorithm cannot achieve pixel-level classification accuracy as image-segmentation methods, it can simultaneously draw minimum bounding rectangles for fruits and damaged regions, providing an effective basis for judging fruit damage severity. YOLOv5s was improved for thermal images. The results showed that the F2-score, mean Average Precision (mAP) and mAP50 of the improved model were 97.76%, 86.24% and 98.08% respectively, superior to the original YOLOv5s. Its computational cost was 1.31 GFLOPs and frame rate reached 160, which were 31.95% and 121.21% of those of the original YOLOv5s respectively.

4. Existing Problems and Future Perspectives

Most existing studies are still at the prototype experimental stage without mature products or systematic solutions. Automatic detection methods based on infrared thermal imaging show obvious differences in algorithm complexity, interpretability, deployment cost, detection duration and generalisation ability.

Image-processing methods make use of texture and morphological characteristics of infrared thermograms with strong interpretability and low deployment cost. However, discrimination rules for extracting damage contours are based on statistical thresholds of features, leading to weak generalisation ability.

Frequency-domain-analysis methods are not affected by heat-source reflection, irradiation power, sample shape, uneven heating and local thermal-emissivity differences, and perform well in detecting subsurface defects at different depths of fruit peels with favourable generalisation [31]. Nevertheless, the experimental equipment required for precise heat-source control is expensive and complicated to operate, accompanied by long detection time.

Combination with traditional machine-learning models can improve model adaptability and accuracy. However, in the process of manual feature extraction, screening and dimensionality reduction, traditional machine-learning may discard useful features. Multi-stage processing tends to cause error accumulation, and has weaker generalisation and lower accuracy under complex scenarios compared with deep-learning methods.

Although the application of deep learning in fruit infrared-thermal-imaging detection is gradually increasing, most researches focus on image classification. Segmentation or object-detection studies for extracting damaged regions are still in the exploratory stage. In addition, the training and generalisation of deep-learning models highly rely on large-scale annotated datasets, while annotated datasets for fruit infrared-thermal-imaging detection are still scarce, which seriously restricts model training and performance improvement. Further in-depth research is still needed in model adaptation and robustness enhancement. Deep-learning training and inference also require high computing power.

To improve the practical application capacity of infrared-thermal-imaging-based fruit detection, standardised detection procedures should be formulated to standardise detection steps and ensure data reliability, laying a foundation for large-scale application. On this basis, machine-learning and deep-learning technologies should be integrated. Adaptive research should be carried out according to the physiological characteristics of different fruits to develop more robust detection algorithms and improve system stability and accuracy. Through these measures, infrared thermal imaging is expected to become a core technical breakthrough point for large-scale fruit quality detection and provide strong support for benefit improvement.

5. Conclusions

Thermal imaging is a versatile and practical non-destructive detection technology for fruit quality. This paper summarises the research progress of signal-processing algorithms and automatic identification-modelling algorithms for infrared thermal imaging based fruit detection in recent years. Combined with advanced machine-learning technologies, infrared thermal imaging has achieved rapid development. It can realise efficient non-destructive detection of fruit maturity, rot, bruising and damage degree, and overcome technical bottlenecks in non-destructive detection of dark-coloured fruits. With the continuous development of deep-learning and deeper understanding of fruit biological characteristics, further research and optimisation based on high-quality and large-scale infrared thermal image datasets is expected to lead the transformation of fruit industry, improve fruit quality, reduce post-harvest losses and play a greater role in smart agriculture.

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