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Adaptive neuro-heuristic hybrid model for fruit peel defects detection

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HIGHLIGHTS

- Novel methodology based on hybrid model of neural network co-working with heuristic algorithm.
- Model of adaptive neural network to better simulate recognition processes.
- Automated approach to fruit peel defects detection.

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ABSTRACT

Fusion of machine learning methods benefits in decision support systems. A composition of approaches gives a possibility to use the most efficient features composed into one solution. In this article we would like to present an approach to the development of adaptive method based on fusion of proposed novel neural architecture and heuristic search into one co-working solution. We propose a developed neural network architecture that adapts to processed input co-working with heuristic method used to precisely detect areas of interest. Input images are first decomposed into segments. This is to make processing easier, since in smaller images (decomposed segments) developed Adaptive Artificial Neural Network (AANN) processes less information what makes numerical calculations more precise. For each segment a descriptor vector is composed to be presented to the proposed AANN architecture. Evaluation is run adaptively, where the developed AANN adapts to inputs and their features by composed architecture. After evaluation, selected segments are forwarded to heuristic search, which detects areas of interest. As a result the system returns the image with pixels located over peel damages. Presented experimental research results on the developed solution are discussed and compared with other commonly used methods to validate the efficacy and the impact of the proposed fusion in the system structure and training process on classification results.

1. Introduction

Automatic detection and decision support is one of the important applications of Computational Intelligence (CI). Most often in this type of systems we adapt computational power of neural networks to evaluate input data. Sometimes it is possible to combine neural network with other solutions to extend possibilities of composed in this way systems. However CI systems precision and robustness mainly depend on two important aspects: developed model and training process. Fusion of data processing structures can approach to simulate some of human brain abilities, which in the process of education adapts to various situations. Construction of adaptive artificial intelligence is a very complicated task. To compose this type of CI we must solve and implement a system that approaches to simulate adaptation to the input.

Composition of systems able to extract and detect features from images is complex, however we can find various attempts to this by application of neural networks. In Pavel, Schulz, and Behnke (2017) was presented how to compose a neural architecture for extraction of features from segmented images. Various methodologies are more efficient in cooperation, where fusion of ideas influences efficiency of image sensing as discussed in Ghassemian (2016). Allocation of aspects in classification systems can improve overall results, since a fusion of approaches makes it possible to benefit directly from the best features of combined methods as presented in Karakatic and Podgorelec (2016). Neural architectures implemented for reasoning are well known for their efficiency. Training processes can extensively improve overall efficacy of neural networks. One of the most efficient methods applied to various types of neural networks architectures is back propagation. It can be used in temporally encoded networks as presented by Bohte, Kok, and Poutré (2002), weight constraints learning presented by Wu, Maguire, Glackin, and Belatreche (2006), and wide variety of

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image processing systems (Egmont-Petersen, de Ridder, & Handels, 2002).

Modeling of architecture and training makes neural network (alone or in cooperation with other methods as a hybrid solution) efficient controller in various systems. Sarkar et al. (2015) presented dedicated spiking neural architecture and training for tea classification, while Mnih et al. (2015) has shown that it is possible to implement human-level control for multi-agent systems.

1.1. Related works

Detection systems for fruit and vegetable evaluation are continuously developed over the years since the need for efficient automatic assistance is very high. There are reported research on systems for greenhouse cucumber as shown by Zhang et al. (2007); apple blemishes developed by Leemans, Magein, and Destain (1998); fruit color grading composed by Nakano (1997). In this type of systems an important role is given to various neural network architectures which are trained for evaluation purposes. In Miller, Throop, and Upchurch (1998) was proposed an application of neural network architecture to evaluate reflectance characteristics, while Wen & Tao (2000) presented dual-imaging methodology for apple classification. Heuristic methods are efficient in search and are reported to be used in various systems. In Zhang and Zhang (2016) was proposed application of metrics for similarity detection. Heuristics can improve abilities of computer systems for image processing to extract shapes of objects from 2D images, as proposed in Wozniak, Polap, Napoli, and Tramontana (2016). Also visual categorization for shapes in primate cortex is possible if we appropriately model image descriptors as discussed by Sigala and Logothetis (2002). Similarly, these methods were proven to efficiently process multimedia streaming and images of various types, Bhandari, Singh, Kumar, & Singh (2014) applied this to satellite image segmentation.

In this article we present our research on adaptive system for detection of features of interest in input images. As a research object we have chosen damages in peel of three fruit kinds: apple, banana and orange. The novelty of the proposed solution is in the developed hybrid methodology, its composition and following stages of processing for which we have composed adaptive neural network and heuristic detector.

The solution we present is based on proposed adaptive neural network architecture that evaluates segments of input images to forward selected ones with potential peel damage to the heuristic detection method which detects these changes. Input images are first decomposed into segments, since in smaller images (decomposed segments) we need to process less information. For each segment a descriptor vector is composed to be presented to proposed neural architecture. Evaluation is run adaptively, where proposed network adapts to inputs and their features. After evaluation, selected segments are forwarded to heuristic search, which detects areas of interest. As a result the system returns recomposed image with pixels located over peel damages. We have considered changes in peel outlook, which are visible in the changes of the texture, color, etc. There are possible various differences like surface defects caused by mechanical interaction, morphology defect, peel color defect, mold and more. However in our research we did not distinguished them in various categories but all of them recognized as a defect. In our idea, proposed model is to find possible defects and show its occurrence in the peel, while final decision on classification of the defect is to be taken by the system operator.

In the following sections we present proposed input image segmentation, describe how the input image can be decomposed into segments for which descriptors are calculated to represent features important for information processing. Next section is to present developed model of Adaptive Artificial Neural Network (AANN), where we discuss proposed architecture and topology with implemented adaptive training process. Then we present a heuristic method to detect features of interest. Presented experimental results and comparison of developed solution with other commonly applied methods help to draw conclusions and summarize our research on adaptive neural architectures for machine learning development.

2. Input image segmentation and descriptors set construction

Each image has many features that all bring various information about the context, however it is not possible to use all of them for evaluation. To enable fast processing on the developed adaptive neural network we need to have possibly low dimension descriptor. Therefore in proposed solution we introduce segmentation of the input image. Picture I is segmented into parts Seg_s, $s = 1, \ldots, S$ and after that each of them is given descriptors presented in Fig. 1. In this way we compose a set of small images with information of the context that can be faster processed using developed solution.

In the beginning, each Seg_s is measured to calculate the number of h pixels in height and the number of w pixels in width. Then for each of the segments, using information about primary colors (*Red*, *Green*, *Blue*) we calculate values (*Hue*, *Saturation*, *Brightness*). Khotanzad and Hong (1990) proposed efficient recognition method based on Zernike descriptors, however proposed technique is devoted to shape recognition while here we propose a solution to classify potential peel defects. Therefore we would like to introduce descriptors based on basic image features. Let us first introduce two measures

$$\begin{cases} \delta = \max\limits_{\mathbf{x_p^s} \in Seg_s} (R(\mathbf{x_p^s}), G(\mathbf{x_p^s}), B(\mathbf{x_p^s})) \\ \eta = \min\limits_{\mathbf{x_p^s} \in Seg_s} (R(\mathbf{x_p^s}), G(\mathbf{x_p^s}), B(\mathbf{x_p^s})) \end{cases} \tag{1}$$

that represent the maximum and the minimum of primary colors in a segment.

We introduce *Hue* measure $H(\cdot)$ for $\mathbf{x_p^s} \in Seg_s$ as the angle on the color wheel which takes a value between $\langle 0^\circ, 360^\circ \rangle$. The color wheel begins with red color and subsequently at 120°moves to a different color, e.g. 120°is green and 240°is blue.

$$H(\mathbf{x_p^s}) = \begin{cases} 60^\circ \left[\dfrac{G(\mathbf{x_p^s}) - B(\mathbf{x_p^s})}{\delta - \eta} (\bmod 6) \right] & \text{if } \delta = R(\mathbf{x_p^s}) \\ 60^\circ \dfrac{B(\mathbf{x_p^s}) - R(\mathbf{x_p^s})}{\delta - \eta} + 2 & \text{if } \delta = G(\mathbf{x_p^s}) \\ 60^\circ \dfrac{R(\mathbf{x_p^s}) - G(\mathbf{x_p^s})}{\delta - \eta} + 4 & \text{if } \delta = B(\mathbf{x_p^s}). \end{cases} \tag{2}$$

In case when $\delta - \eta = 0$, it is considered that the value is indeterminate.

Introduced measure of *Saturation* $S(\cdot)$ for $\mathbf{x_p^s} \in Seg_s$ is a radius of the base that takes values of $\langle 0, 1 \rangle$ calculated as

$$S(\mathbf{x_p^s}) = \frac{\delta - \eta}{1 - |\delta + \eta - 1|}, \tag{3}$$

where for $\delta = \eta$ we have $s = 0$.

Introduced measure of *Brightness* $B(\cdot)$ for $\mathbf{x_p^s} \in Seg_s$ is interpreted as a height of the color cone. Similarly to *Saturation*, it takes values in the range $\langle 0, 1 \rangle$. It is defined as the average value of the largest and the smallest components of color what can be represented in the following formula

$$B(\mathbf{x_p^s}) = \frac{\delta + \eta}{2}. \tag{4}$$

Having these we can define descriptors D_j^s for the input image I pixels $\mathbf{x_p^s} \in Seg_s$ for $p = 1, \ldots, h \cdot w$, which are developed to give possibly most useful information for peel defects detection.