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ОТКРИВАНЕ НА ОГЪН С ПОМОЩТТА НА ИЗКУСТВЕНИ НЕВРОННИ МРЕЖИ

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FINDING FIRE WITH THE HELP OF ARTIFICIAL NEURAL NETWORKS

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Abstract. Current paper presents an application of Deep Neural Networks in the field of detecting fire in different areas. Using machine vision, combined with Deep Neural Networks makes possible to improve the fire detecting using a camera.

Key Words: Deep Neural Networks, R-CNN, object detection, classification, fire detection

INTRODUCTION

Fire can be caused by multiple sources and for preventing fire spreading, a fire extinguishing system is needed to be used. Most systems for fire detection are based on sensors but in the recently years fire can be detected using a single camera and a well-trained neural network for fire recognition. This paper presents a neural network that creates a pixel mask over the flaming objects in the image.

OVERVIEW

Industrial facilities and nature can always threat by the fire because of different reasons. Sensors may not always be highly efficient thus the development of more advanced methods for fire detection are necessary. Artificial neural networks (ANN) are very efficient in finding various objects and can be used for detecting fire. They can replace any expensive sensors by just using a surveillance system. Once a fire has been found the ANN can automatically show a picture of where the fire is and activate the needed actions for preventing the burning thread from spreading. These actions can control different types of fire extinguishers including acoustic fire extinguishing [1].

ARCHITECTURE OF MASK R-CNN

The mask R-CNN is a deep neural network used for solving instance segmentation problems in computer vision separating objects in a video or image. It is based on Faster R-CNN architecture with two major changes :

- It replaces the ROI pooling module with a more accurate ROI Align module
- Inserting an additional branch out of the ROI Align module

The additional branch accept the ROI output and then sends it into the convolutional (Conv) layers. The mask is the output of the Convolutional layers. Acquired image is processed by the neural network and recognized objects are masked on the image.

Mask R-CNN has two stages.

1 – Generating proposals where the regions might be in a object based on the input image.

2 – Predicting the class of the object and refines the bounding boxes generating a pixel level mask of the object in the first proposal.

This network is a Feature Pyramid Network (FPN) style deep neural network. It consists of a bottom-up pathway , a top-bottom pathway and lateral connections. Bottom-up pathway can be any ConvNet, usually ResNet, which extracts features from raw images. Top-bottom pathway generates feature pyramid map which is similar in size to bottom-up pathway. Lateral connections are convolution and adding operations between two corresponding levels of the two pathways. FPN outperforms other single ConvNets mainly for the reason that it maintains strong semantically features at various resolution scales. At the first stage a light weight neural network called RPN scans all FPN top-bottom pathway and proposes regions which may contain objects. While scaning it is also needed a method to bind features to its raw image location. This is achieved using anchors. They are a set of boxes with predefined locations and scales relative to images. Ground-truth classes(only object or background binary classified at this stage) and bounding boxes are assigned to individual anchors according to some value. As anchors with different scales bind to different levels of feature map, RPN uses these anchors to figure out where of the feature map 'should' get an object and what size of its bounding box is. At the second stage, another neural network takes proposed regions by the first stage and assign them to several specific areas of a feature map level, scans these areas, and generates objects classes (multi-categorical classified), masks and bounding boxes. The procedure looks similar to RPN. Differences are that without the help of anchors, stage-

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two used a trick called ROIAlign to locate the relevant areas of feature map, and there is a branch generating masks for each objects in pixel level (fig. 1).

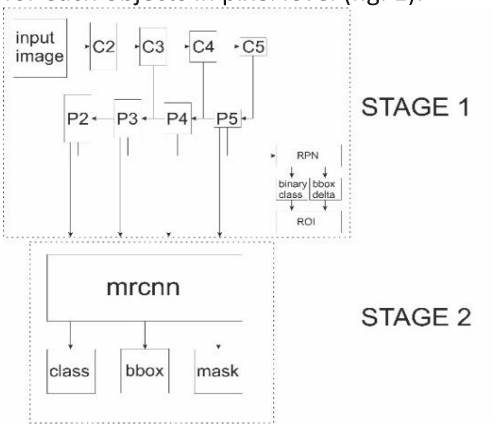

Fig 1. Architecture of MASK R-CNN

The neural network is an extension to the Faster R-CNN. The faster R-CNN can only predict bounding boxes while the Mask R-CNN in parallel predicts the object mask.

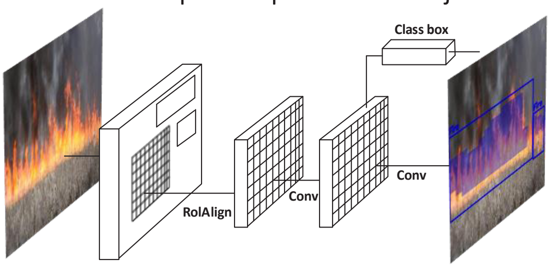

Fig 2. Mask R-CNN framework for instance segmentation

USED LIBRARIES FOR FIRE DETECTION

To implement the presented algorithm (fig. 3) are used several software technologies. For processing of images is used OpenCV. This is an open source computer vision and machine learning library. It is designed to provide a common computer vision application infrastructure and accelerate machine perception. The library has more than 2,500 optimized algorithms that include a comprehensive set of classical and advanced computer visions and machine learning algorithms. It has C ++, Python, Java and MATLAB interfaces and supports Windows, Linux, Android and Mac OS. OpenCV mostly relies on real-time vision applications. There are over 500 algorithms and about 10 times more features that compose or maintain these algorithms [2].

Numpy is a library for the Python programming language, supporting multi-dimensional arrays. Using NumPy we can display the images as multidimensional arrays. With NumPy built-in mathematical functions at a high level, numerical analysis of the image can be performed quickly and easily.

Matplotlib is a separating library. When analyzing an image, Matplotlib is used regardless of whether it separates the image from histograms or simply opens the image itself. Imutils is a library with common features such as rotation and resizing.

TensorFlow - TensorFlow is an end-to-end open source platform for machine learning. It has a comprehensive, flexible ecosystem of tools, libraries and community resources that lets researchers push the state-of-the-art in ML and developers easily build and deploy ML powered applications.

ALGORITHM

The algorithm starts with initialization of entire system. When initialized the application is started it reads a video signal from a USB camera that can be USB IP or any other type. The acquired video frame is being resized and scanned by the trained mask R-CNN neural network. It is trained to recognize flames in the image. When a flame is detected with high percentage to be an actual frame its pixels coordinates are returned by the neural network. The application program draws a rectangular frame around the detected fire mapping all fiery pixels inside it and activate an alarm for fire extinguish.

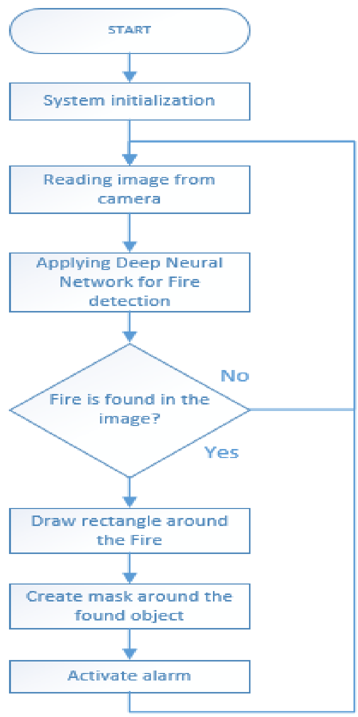

Fig. 3. Algorithm of operation

TRAINING THE NEURAL NETWORK

A neural network has been trained with Mask R-CNN architecture which has high speed for detecting various objects [3]. The training requires a preliminary database of photos (some of them shown on fig 4) from which it is necessary to extract the characteristics of the objects which have to be found after that. It also requires to create annotations of the mask in every image. The neural network is trained using the library for machine learning TensorFlow.The neural network is able to recognize multiple objects and by doing software filtering which object is one from the trained list is fire and which is not in the image.

Fig. 4. Some of the photos for training the neural network

The well-trained neural network can be implemented in various places (CPU, GPU, VPU).

EXPERIMENTAL RESULTS

For training the neural network for finding fire 60 images were used extracting their characteristics and pixel annotations training an neural network with Mask RCNN Inception architecture for 45 000 cycles until reaching the desired accuracy. The system can detect objects at a different instance. The neural network was tested with the following images which they were not included while training. On fig 5 is shown fire detection in a simple image for basic testing without other objects in it.

Fig. 5. Fire detection

For the second test of the neural network, a image with a fire in the living room and other objects was chosen for testing which result can be viewed on fig 6.
For the third test a picture of a burning rooftop during daylight was used and the results can be seen below.
The neural network was implemented in a video surveillance system for fire detection which can run on different platforms. On fig 8 is shown a image from a video with burning objects.

Fig. 6. Fire detected in a living room

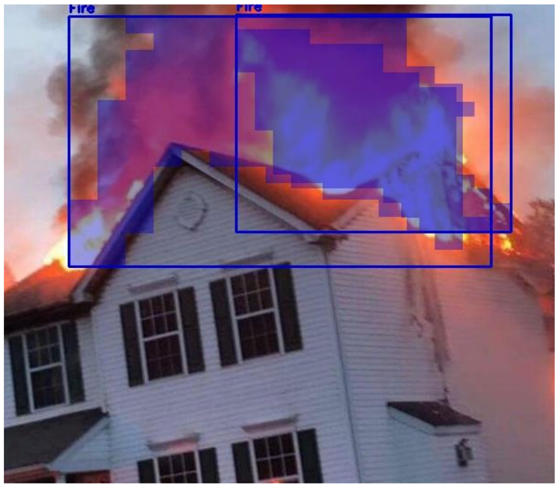

Fig 7. Fire detection on a burning house

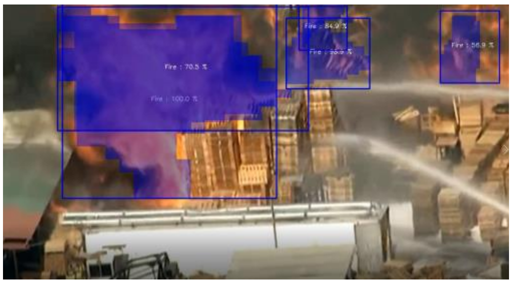

Fig. 8. Top view of burning buildings.

CONCLUSION

The proposed neural network is very high reliable for detecting fire and can be integrated in modern anti fire systems replacing expensive sensors.The vision system uses low-cost components and commercially available technologies for detection of fire with high efficiency. This system can be implemented in high temperature facilities such as foundry, dryersand and production with heat treatment.

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ИНТЕЛИГЕНТНИ МЕТОДИ С ПРИЛОЖЕНИЕ В МУЛТИСЕНЗОРНИЯ АНАЛИЗ НА ХРАНИ

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INTELLIGENT METHODS APPLIED IN MULTISENSOR FOOD ANALYSIS

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Abstract: This paper looks at some of the most important aspects related to sensory characteristics and examples of applications to define the quality of food products. The purpose of the study is exploring the possibilities of combining data from different sensors in order to increase the accuracy of classification of food products.

Key words: food quality, sensory analysis, multisensory analysis, e-nose, e-tongue

ВЪВЕДЕНИЕ

Анализът на храните е интензивно развиваща област, което е в съответствие със съвременните изисквания за тяхното качество, безопасност и здравословност. Основната цел при анализа на хранителните продукти е осигуряване на информация за широк спектър от характеристики или процедури като установяване на легалност и съответствие на етикетиране, оценка на качеството, детерминиране на компонентно съдържание, установяване на автентичност и идентичност, състав, физико-химични свойства, сензорни атрибути и др. Тази информация е от решаващо значение за рационалното установяване на факторите, определящи свойствата на храните, тяхната безопасност и информативност при избора им. Според една от дефинициите за качество касаеща хранителни продукти най-общо то представлява набор от определени показатели измерени с обективни критерии, определящи състоянието на продукта, приемливо и очаквано за потребителя. В тази връзка обекта на изследване са такива методи, с които могат да се определят характеристики корелиращи с органолептични оценки, вътрешно качество, хранителна стойност, химически състав, механични свойства, функционални качества и дефекти. В определени случаи с тези методи може да се постигне една интегрална оценка т.е. определяне на повече от една характеристика посредством един и същ инструментален метод.

В последните години при анализа на храни засилено започна да се прилага спектралния и сензорния анализ („електронен нос” и „електронен език”) за определяне на някои основни свойства на продуктите. Изследвани са в определени задачи и техните възможности за дефиниране на технологични качества, фалшификации, бактериално развитие, развалата (преснотата) и други [2,6]. Традиционно използваните досега сензори (ултразвукови, оптични, микровълнови, лазерни и др.), бяха усъвършенствани като възможности и съвместимост с компютърните технологии и съвременните методи за обработка на данни, което доведе до възприемане на понятието интелигентни сензори [1,7,8]. В голяма степен съвременните средства позволяват процеса на синтез в съвременните системи за окачествяване да се доближи до парадигмата на човешката сензорна система.

Сензорните характеристики по същество представляват свойства, възприемани от човешките сетивни органи (външен вид, аромат, вкус, текстура). Сензорната система на човека използва разнообразна входяща информация при вземане на решение. Интерпретирането на тази информация, получена от сетивните органи на човека в неговия мозък, с цел приемане на крайно решение не е нещо тривиално. Само за определянето на показателя „степен на зрялост“ се използват множество свързани показатели като цвят, аромат, размери, маса, блясък и др. Такава интелигентна, т.е. присъща на човека обработка поражда идеята за осъществяване с т.нар. „сензорно обединяване“ (*sensor fusion*) [8,9]. В този процес се смесват и интегрират сигнали от множество различни източници. Информацията, получена от мултисензорна система се преработва чрез алгоритми, които могат условно да се разделят на две групи: сензорно обединяване, основаващо се на вероятно-статистически модели и сензорно комбиниране на базата на интелигентни модели. В последните няколко десетилетия в инженерната практика все по-често се прилагат подходите, при които се обединяват данните от измерванията на различни сензори, за да се получи оптимална оценка на качеството в статистически смисъл [1,9].

В статията се разглежда един подход за използване на мултисензорно обединяване на данни с цел получаване на интегрални оценки и повишаване информативността на признаците използващи данни от различни по тип сензорни данни.

МАТЕРИАЛИ И МЕТОДИ

Система „електронен нос“. Мирисът е едно от основните органолептични свойства, което се възприема от сетивата на човека. Идентификацията на дадена миризма има широко приложение – за оценка на състоянието и качеството на атмосферния въздух, здравеопазване, медицинска диагностика, екологичен мониторинг, качество на храни, фармация, детекция за наличие на опасни газове и др [10,11].

Нарастващият през последните години интерес на индустрията към качеството на храните по отношение на създаването на полезни техники за разпознаване на миризми и елиминирането на субективния фактор в досегашната практика, както и скъпо струващите лабораторни анализи с помощта на газови хроматографи, доведе до създаването на инструментариум, имащ висока