

The Anomaly Detection of DeepIG Technique in Collaboration of Deep Learning with Machine Learning Technique

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Abstract: A program for identifying abnormalities in crowd action videos provides a way to spot anomalies and warns people to safety at mass gatherings. First we construct a predictive model based on standard (non-anomalous) training knowledge and then identify anomalies using the input data extraction feature. However some natural data got variations that can minimize prediction accuracy. We use SVM Classifier-based prediction models to deal with this problem. To order to extract attributes and spot anomalies from the video at the outset, the deep information gathering (DeepIG) technique is used and alerts are set to order to avoid losses. The program recommends frames of video data to track anomaly fighting running shouting and shooting. If a video includes one of the explosion, war, protest, and run anomalies, the anomaly is identified by the use of the SVM classification from specified video frames. Therefore, with computerized vision-based deep learning and machine processing technologies the proposed system can detect video anomalies. We are proposing a new method for determining the correct anomaly detection predictive model. In advance, our method proposes several expected value candidates and chooses the one nearest to the calculated value. DeepIG chooses the right features for improving prediction accuracy using this definition for abnormal identification. The proposed method measures irregularities more reliably than the comparable approaches in our experimental Evaluation of real data.

KEYWORDS: DeepIG, Anomaly detection, Prediction accuracy, abnormal identification, SVM Classifier.



Check for updates

DOI of the Article: <https://doi.org/10.46501/IJMTST0706062>



Available online at: <http://www.ijmtst.com/vol7issue06.html>



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To Cite this Article:

S.Hemamalini; A.Mehar Nisha; D.Ragavi; M.Suwathi and S.Senthil Srinivasan. The Anomaly Detection of DeepIG Technique in Collaboration of Deep Learning with Machine Learning Technique. *International Journal for Modern Trends in Science and Technology* 2021, 7, 0706113, pp. 375-379. <https://doi.org/10.46501/IJMTST0706062>

Article Info.

Received: 19May 2021; Accepted: 22 June 2021; Published: 27 June 2021

INTRODUCTION

INFORMATION gathering (IG) with Self-Governing mobile robots has come up as a prime alternative to cluster information in situations that have a hovering risk for humans, like e.g. rescue missions, and for applications in which it is durable to reduce required time and manpower, like e.g. in environmental analysis. In such context, IG can clearly benefit from multi-robot coordination both in terms of efficiency to Cluster information and robustness against robotic collapse. Information gathering with multiple robots (MR-IG) has been examined for a large range of applications such as surveillance, tracking, monitoring, to name only a few. In particular, in this paper we apply on MR-IG to monitor a physical process of interest like example temperature magnetic field, terrain profile, ozone concentration, etc. Note that in the remainder of the letter we refer to “monitor a physical process of interest with multiple robots” as MR-IG.



Fig. 1. A quadcopters cooperating to map an unknown terrain profile that we built in our field. Quadcopters run an instance of DeepIG, which uses deep learning to teach robots how to gather information efficiently, while avoiding inter-robot collisions.

Modernization MR-IG algorithms belong to the family of model-based algorithms. Most widely used classes of algorithms are Gaussian processes (GPs) [1], [2], and Partially Degrading Markov Decision Processes (POMDPs) [3]. Model-based algorithms assume an fundamental model that describes physical properties of the process, such as spatial and temporal correlation, states' transition function, etc. Given a model, IG algorithms exploit it to derive MR coordination

strategies that allow robots to gather information by optimizing some formal IG criterion.

Model-based approaches are designed to exploit properties of a particular model. This has the advantage of achieving a high performance in applications where the model accurately describes the observed process. In contrast, model-based approaches fail to gather information of processes that cannot be accurately described by existing models.

In a future robotics society, robots will need to solve new IG tasks, and, of course, many of them will not be described by existing models. This implies that we humans will have to invest our time and efforts to develop novel models and corresponding IG algorithms. Additionally, many of the new IG tasks will be too complex to be described by traditional models like aforementioned GPs or POMDPs. Nonetheless, we would like to be able to offer, fast and with limited effort, sufficient algorithms to solve most of the MR-IG tasks that will be demanded by a prospective robotics society.

DEEP LEARNING

Deep learning is an artificial intelligence function that replicate the gadgets of the human brain in processing information and building patterns for use in selection making. Deep learning is a subset of machine learning in artificial intelligence (AI) that has networks skillful of learning individualized from data that is unstructured or unfabled. Also known as deep neural learning or deep neural network. Deep Learning, as a branch of Machine Learning, employs algorithms to process information and act like the thinking process, or to develop cogitations. Deep Learning (DL) uses sheet of algorithms to process information, grasp human speech, and visually perceive objects. Information is passed through each layer, with the turnout of the previous layer providing input for the next layer. The first layer in a network is labeled as input layer, while the last is labeled an output layer. All the layers between the two are point out to as hidden layers. Each layer is typically a simple, uniform algorithm containing one kind of stimulating function. First we have to take input as a video from robot and we have to get information from the robot, we convert the video as a image. First we have to take input as a video from robot and we have to

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Dataflow Diagram

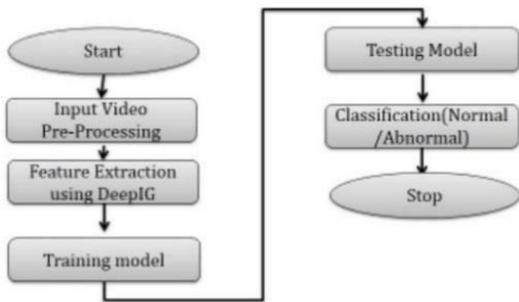


Fig. 2. Data flow diagram deep IG Process which classify normal and abnormal status

These images are divided into pixel and the robots will be trained to classify according to the classifier model and SVM classifier model. The neural networks are classified into 3 layers. They are 1.Input layer 2.Hidden layer 3.Output layer. It finds whether the place and people are normal and abnormal. Then we get output as a video.

and Actuators Module. Actuators decode a robot’s planned action into a robot’s migration. Sensors and communication (S&C) modules.

B. Reward Generator

We propose a reward that Accomplish our two main target: (i) efficient MR- IG, and (ii) effective inter-robot percussion avoidance. Note that each robot m sprint an instance of DeepIG

This implies that rewards are generated for a specific robot. As we stated in Sec. II, our goal is to efficiently reduce the NRMSE between process P and process estimate P’.

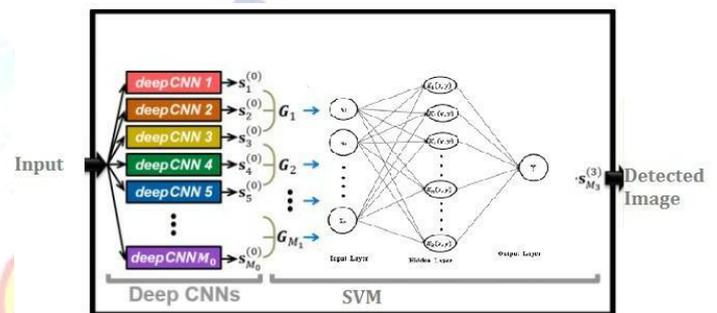


Fig.4.Deep CNN vs SVM from input to Detected image.

ARCHITECTURE DIAGRAM

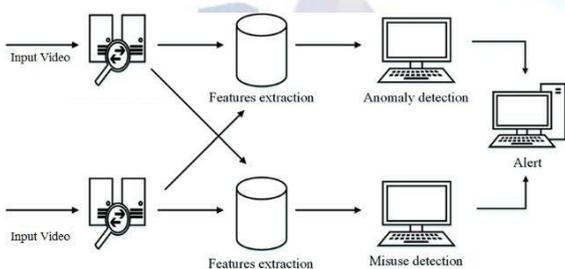


Fig 3.The detailed architecture of input video from surveillance camera features extraction

DEEP IG ALGORITHM

A.Overview

DeepIG is a MR-IG algorithm. In particular, each single robot runs in lateral an duplicate instance of DeepIG, and inter- robot planning is done by means of inter-robot conversation. In Fig.2 we depict a block diagram of DeepIG. Next let us explain DeepIG in more structured. Sensors Module, Communications Module,

Deep learning (DL) has become a common word in any investigative or business since project argument. It belongs to a deep Artificial intelligence field of research and part of machine learning algorithms to be special. These models are purely based on learning figure and representations found in the given representations x (understand the data patterns vs. furniture a line, hyper plane or a decision boundary)compared to task-specific algorithms. Learning can be supervised, semi-supervised and unsupervised.DL models play a vital role in computer vision, speech recognition, natural language processing, bioinformatics, drug-design and machine translations to list a few.

In simple terms, most deep learning models involve stacking multiple layers of neural nets in a particular architectural layout for either a prediction or classification problem (Reinforcement and Generative architectures deal with a different set of real-world problems). Neural nets are skillfull,fast and scalable and they can handle high proportional tasks with ease (an extreme number of feature set; i.e., in object recognition – identify whether an image contains a cat or dog, each

pixel colour channel will be a feature; a 120x120 image leads to a matrix of 14400 pixels and multiply that by three for RGB channel intensity. we will end up with 43200 features to start with)

NEURAL NETWORK

A neural network is a sequence of algorithms that acts to recognize essential relationships in a set of data through a process that imitates the way the human brain operates. In this logic, neural networks refer to systems of neurons, either organic or artificial in nature. Neural networks can adjust to shifting input so the network creates the best possible result without needing to rewrite the output criteria. The idea of neural networks, which has its roots in artificial intelligence, is swiftly gaining popularity in the development of trading systems. Neural networks, in the world of deal, assist in the development of such process as time-series forecasting, algorithmic trading, securities classification, credit risk modeling and constructing proprietary indicators and price spinoffs'. A neural network works similarly to the human brain's neural network. The network bears a strong similarity to statistical methods such as curve fitting and regression analysis.

SVM CLASSIFIER

The Data are analysed using machine learning algorithm are administrated by learning models. Assigning new categories to SVM algorithm shapes a model with sample examples. Making it a non-probabilistic binary linear classifier it uses SVM in a Probabilistic classification setting. The isolated categories are divided by a clear gap. In totalling to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. implicitly mapping their inputs into high-dimensional feature spaces. When data are unlabelled, supervised learning is not possible, and to find natural clustering of the data to groups, an unsupervised learning approach is required and new data is formed.

PRE PROCESSING

The video must be pre-processed for noise reduction , and used for the purpose of converting in to structured

one ((i.e) video in to image blocks) and then mapping the Images in to next process.

INFORMATION GATHERING

Information gathering is the fundamental task in a wide range of applications such as environmental monitoring, or rescue missions. Information gathering with video can be utilized to monitor physical processes of interest. proposed multi- robot information gathering algorithm is called deepIG.

FEATURE SELECTION

After Pre-processing, the characteristics of the images can be observed, and then feature selection can be made for dimension pixels data set is extraction

CLASSIFICATION

For Classification, we utilize neural network that maps environment's observation to robots actions. At each step, an agent inputs a frame of the environment's observation to the deep neural network. neural network will output the probability with which every action should be taken by the agent for the particular input. Besides it will output the value corresponding to the environment's state represented by the input and the rewards encodes whether the action taken by the agent is good or bad

CONCLUSION AND FUTURE WORK

We introduced in this letter DeepIG, a information gathering algorithm. DeepIG uses deep learning to learn how to gather information, while avoiding inter-robot collisions. DeepIG employs *limitation allocation learning*, and extends state-of- the-art A3C algorithm to account for multiple automatons that carry out an IG task. This *extension we named it MR- A3C*. Additionally, we can implement a coloring algorithm to render measurements values as an image. The agent is a module responsible of deciding the next robot action. We have a global deep neural network that is common to all basic units. On the other hand, each basic unit has a copy of the global network. It is the local neural network the one that is utilized by agents to select actions, generate experiences, and to calculate gradients. Then gradients are used to update in parallel and asynchronously, the global network.

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