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A Survey of Artificial Neural Networks and Semantic Segmentation

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Abstract: An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems. Tasks that requires human like intelligence or trends that are too complex to be noticed by either humans or other algorithm techniques can be solved by the remarkable ability of neural networks to derive meaning from complicated or imprecise data, and this can be used to extract patterns from the given data. A trained neural network can be thought of as an expert in the category of information it has been given to analyses. This expert can then be used to provide meaningful information from an image or video Segmentation is a partition of an image into several coherent parts in terms of low-level cues such as colour, texture and smoothness of boundary. Semantic segmentation tries to rupture the image into semantically purposeful parts and classify each part into one of the pre-determined classes. This process achieves the segmentation goal by classifying the image in a pixel level rather than the entire image. Semantic segmentation is a complex task requiring knowledge of support relationships and contextual information, as well as visual appearance. Early methods that relied on low level vision cues have fast been superseded by popular machine learning algorithms. Deep convolution neural network can be employed to perform such machine learning tasks semantic segmentation. The challenge in performing semantic segmentation is that the scene may contain foreign objects as well as scenes often vary significantly in pose and appearance. This survey gives an overview over different techniques used for pixel-level semantic segmentation and hierarchy of artificial neural networks. The very recent approaches with convolution neural networks are mentioned which is widely being used now and the taxonomy of segmentation algorithms is given.

Keywords: Semantic segmentation, Convolution neural network, Artificial neural network, Deep convolution neural network, Machine learning

I. INTRODUCTION

A Convolution neural network (ANN) is a flexible mathematical design which is adequate to determine complex nonlinear relationships between input and output data sets. ANN models have been found appropriate and efficient, especially in problems for which the aspects of the processes are strenuous to portray using physical equations. Robotics and digital systems have been partially or fully simulated by these kinds of human like intelligence providing systems. In analogy with conventional computers neural network take a very contrasting approach. Conventional computers use algorithmic approach or step by step approach whereas, one should feed the computer with specific steps to follow to solve the problem [1]. This restricts the conventional computers problem solving capability that we already understand how to solve. Neural networks mimic the behavior of human brain. The networks solve a problem by processing elements or neurons which works parallel. Neural networks cannot perform a specific task and it learns by illustrations. For this reason, neural networks should be trained correctly or the precedent should be selected carefully for the equitable functioning. The detriment is that because the network finds out how to solve the problem by itself, its operation can be uncertain.

Image segmentation is an important image processing technique, and it is used when there is a need to analyze what is inside an image. It is the process of partitioning a digital image into multiple segments, set of pixels, also known as super pixels, which are homogeneous with respect to some criterion. In addition, image segmentation methods can be applied to traffic control systems [2], machine vision [3], localization of objects in satellite images and so on. Different algorithms have been proposed for image segmentation such as those based on image threshold (e.g. by means of histograms of gray levels); region growing methods; edge based segmentation and graph partitioning methods. Most of these methods present some drawbacks and do not provide accurate segmentation. Semantic segmentation has a wide range of applications including scene understanding, inferring support-relationships among objects, volumetric analysis to autonomous driving [4]. Early methods that relied on low level vision cues have fast been superseded by popular machine learning algorithms. Deep learning has seen huge success lately in handwritten digit recognition [5], speech, categorizing whole images and detecting objects in images [6]. Now there is an active interest for semantic pixel-wise labeling.

Different techniques are used for pixel-level semantic segmentation. Metrics and data sets are used for the evaluation of segmentation algorithms. Traditional approaches for segmentation include unsupervised methods, Decision Forests and Support Vector Machines. Recently published approaches with convolution neural networks are gaining more attention today. Convolution neural networks are neural networks which learn image filters. They drastically reduce the number of parameters which must be learned for the specified task while being still general enough for the problem domain of images.

The semantic segmentation method can be passed down to perform volumetric segmentation also. The current ongoing challenge in the computer vision based product recognition problem is inefficient performance in identifying the volume of the products as well as noises in the image which may mislead accurate prediction. Neural networks disciplined for such segmentation task perchance used for retail business case also. Currently, semantic segmentation has proven to be a very useful framework for self-driving cars for identifying the road scenes correctly. Semantic segmentation is basically the task of clustering and classifying parts of images together which belong to the same object class. This type of algorithm has several use cases such as road signs detection as mentioned above, tumor detection [7], detecting medical instruments in surgeries [8], land cover, land use classification [9] and colon crypts segmentation [10]. Non-semantic segmentation, in contrast only clusters and classify pixels together based on general characteristics of single objects which doesn't have any task specific meanings. Hence the task of non-semantic segmentation is not well-defined, as many different segmentation might be acceptable which is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

Object detection, in juxtaposition to semantic segmentation, must analyze contrasting instances of the same object. Semantic segmentation is assuredly a big leverage when demanding to get object instances, there are a couple of obstacles: adjoining pixels of the same class might belong to disparate object instances and regions which are not connected may belong to the same object instance. For example, an electric post in front of a vehicle which optically segregate the car into two components.

It shows that fully convolution networks (FCNs) trained end-to-end, pixels-to-pixels on semantic segmentation exceed the previous best results without further machinery. This is a study on semantic segmentation and artificial neural networks and how neural networks can perform segmentation in a pixel to pixel manner. Fully convolution versions of existing networks predict dense outputs from arbitrary sized inputs. Both learning and inference are performed whole-image-at-a-time by dense feed forward computation and back propagation. In-network up sampling layers enable pixel wise prediction and learning in nets with sub sampling.

II. ARTIFICIAL NEURAL NETWORK

Convolution Neural Networks(CNN) are buildup of neurons that have learnable weights and biases which help these networks to learn patterns. Each neuron seizes some inputs, calculates the dot product and deliberately pursue it with a non-linearity. All conspiracy's that are advanced for learning regular Neural Networks also apply.

III. TYPES OF ARTIFICIAL NEURAL NETWORKS AND ITS APPLICATIONS

Convolutional neural network is a class of static convolution neural network all coming under the category of Artificial neural network. Neural Networks are a computational approach which is based on a large collection of neural units loosely modeling the way the brain solves problems with large clusters of biological neurons connected by axons. Each of the neuron is connected to many others and the links between them can be invoking or in inhibitory in their consequence on the activation state of associated neurons. Individual neurons in the network may have a summation function which fuse the values from all its inputs. There is a chance for each connection to have a threshold function or a bar function such that it must outweigh it before it can inseminate to alternative neurons. Unlike conventional computer programs in which feature detection or pattern recognition is a challenging task, conventional neural networks learn itself and trained rather than explicitly programmed and outdo these kinds of tasks.

The network term indicates the interconnection between neurons in different layers of the system. The very first layer send data via synapses to the second layer of neurons and the second layer sends the data to the subsequent layers via synapses until it reaches the output layer of neurons. More complicated systems will have more hidden layers and the network architecture will also be different. The synapses that propagate the data through the network store parameters called "weights" that wield the data in the calculations.

An ANN is typically defined by three types of parameters:

- The interconnection pattern between the different layers of neurons.
- The learning process for updating the weights of the interconnections.
- The activation function that converts a neuron's weighted input to its output activation.
- Learning paradigms: There are three major learning paradigms, each corresponding to an abstract learning task, supervised learning, unsupervised learning and reinforcement learning respectively.

There are neural networks with only one or two layers with single direction logic and networks having convoluted multi input many layer feedback loops and layers. Overall, these systems use algorithms in their programming to determine control and organization of their functions. Most systems use "weights" to change the parameters of the throughput and the varying connections to the neurons. Artificial neural networks can be autonomous and learn by input from outside "teachers" or even self-teaching from written-in rules.

A. *Dynamic Neural Network*

Dynamic neural network deal with time-dependent behavior such as various transient phenomena and delay effects. Techniques to estimate a system process from observed data fall under category of system identification. This is again classified into seven categories which is given below [11].

- Feed forward neural networks(FNN): A feed forward neural network is an artificial neural network wherein connections between the units do not form a cycle [12]. As such, it is different from recurrent neural networks. The feed forward neural network was the first and uncomplicated breed of artificial neural network crafted. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. Unlike complex neural networks feed forward networks has no cycles or loops.
- Recurrant neural network(RNN): A recurrent neural network (RNN) is a class of artificial neural network where connections between units form a directed cycle. This creates an internal state of the network which allows it to exhibit dynamic temporal behavior. The RNNs can adopt their internal memory to course capricious sequence of inputs. This makes them applicable to tasks such as unsegmented connected handwriting recognition or speech recognition. This again is classified into eight classes; which includes Hopefield networks, which serve as a content-addressable memory

systems with binary threshold nodes; Boltzmann machine which is a stochastic generative counter part of Hopefield networks; Echo state network with a sparsely connected hidden layer; Long short-term memory which is universal in the sense that given enough network units it can compute anything a conventional computer can compute, given that it has appropriate weight matrix, which may be examined as its program; Stochastic neural network, which is a type of feed forward neural network built by introducing random variations into the network, either by giving the networks neurons stochastic transfer functions or by giving them stochastic weights. Other variations of Recurrant neural networks include Simple recurrent networks, Bidirectional RNN and Hierarchical RNN.

- Kohonen Self-Organizing maps: This is a type of artificial neural network (ANN) that is trained using unsupervised learning to crop a low-dimensional (typically two-dimensional), discrete representation of the input space of the training samples, called a map. Self-organizing maps alter from other artificial neural networks as they administer competitive learning as opposed to error-correction learning (such as back propagation with gradient descent), and in the sense that they use a neighborhood function to preserve the topological properties of the input space.
- Autoencoder: An autoencoder, also known as auto-associator is an artificial neural network worn for unsupervised learning of adequate coding. The aim of an autoencoder is to learn a representation (encoding) for a set of data, typically for dimensionality reduction. Learning of generative models of data, widely make use of autoencoder approach.
- Probabilistic neural network (PNN): Probabilistic neural network is a class of feed forward neural network and it is originated form a statistical algorithm labeled Kernel Fisher discriminant analysis and Bayesian network [13]. The operations in PNNs are coordinated into a multilayered feed forward network and this network has four layers. An input layer, hidden layer, summation layer or pattern layer and an output layer. Each neuron in the input layer represents a predictor variable and this layer is responsible for the transfer of data to the hidden layer after processing. The hidden layer stores the value of the predictor variables for each case along with the target value. Summation layer or pattern layer is fed by the hidden layer with weighted values and each neuron in the pattern layer add values to the class they represent. The final layer or output layer acquire weighted votes from the pattern layer and uses the largest vote to predict the target class.
- Time delay neural network(TDNN): The TDNN units recognize features independent of time-shift (i.e. sequence position) and usually form part of a larger pattern recognition system. Conversion of an audio stream into a stream of classified elemental labels for speech recognition cab be taken as an example for this kind of network. An input signal is augmented with delayed copies as other inputs, the neural network is time-shift in-variant since it has no internal state.
- Regulatory feedback network(RFNN): Regulatory feedback networks are neural networks that perform inference using Negative feedback. The feedback is not used to find optimal learning or training weights but to find the optimal activation of nodes. In effect this approach is like a non-parametric method but is different from K-nearest neighbors in that it can be shown to mathematically emulate feed forward neural networks.

B. Static Neural Network

The static neural network has its own class categories;

- Neocognitron: Neocognitron has been used for handwritten character recognition and other pattern recognition tasks, and served as the inspiration for convolution neural networks. The Neocognitron was inspired by the model proposed by Hubel & Wiesel in 1959. They found two types of cells in the visual cortex and scheduled a gush model of these two types of cells. Neocognitron is a natural extension of these cascading models.
- Radial basis function network: Radial basis function network as the name suggests uses radial basis function as their activation function [14]. Linear combination of the radial basis functions inputs and neuron parameters will be the output of the network. The use of Radial basis function network includes time series prediction function approximation, system control, and classification.
- Learning vector quantization: In computer science, learning vector quantization (LVQ) [15], is a prototype-based supervised classification algorithm. LVQ is the supervised counterpart of vector quantization systems.
- Perceptron: In machine learning, the perceptron is an algorithm for supervised learning of binary classifiers. It is a type of linear classifier, i.e. a classification algorithm that makes its predictions based on a linear predictor function combining a set of weights with the feature vector. The algorithm processes elements in the training data set one at a time and this is because it grants online learning [16]. ADALINE or Adaptive Linear Neuron or Adaptive Linear Elements in an early single-layer artificial neural network made up of memistors, which is a combination of memory units and resistors. In machine learning, a convolution neural network (CNN, or ConvNet) is a type of feed-forward artificial neural network in which the connectivity pattern between its neurons is inspired by the organization of the animal visual cortex. Receptive field is a controlled area of space where the cortical neurons respond to stimuli. The receptive fields of different neurons partially overlap such that they tile the visual field. The convolution operation estimates the stimuli within its receptive field of an individual neuron. Convolution networks were inspired by biological

processes and are variations of multi-layer perceptron's designed to use minimal amounts of pre-processing. They have ample applications in image and video recognition, natural language processing and recommender systems.

- Modular neural network: Modular neural network is identified by a series of independent neural networks constrained by some emissary. The task to be solved by the network is taken by these individual neural networks which act as isolated modules and operate on distinct inputs to complete the work the network hopes to perform. The intermediary or emissary in the network takes outputs from each of these individual modules and fuse it produce the output of the entire network. The intermediary only accepts the outputs from the isolated networks and they do not acknowledge to these networks nor otherwise signal, likewise the modules also does not interact with each other. Committee of Machines and Associative neural networks are other variations of the modular neural networks.

C. Memory Networks

Google/Deep mind company has created a neural network that learns how to play video games in a fashion like that of humans, as well as a Neural Turing Machine, or a neural network that may be able to access an external memory like a conventional Turing machine, resulting in a computer that mimics the short-term memory of the human brain. Facebook's Holographic associative memory(HAM) is part of the family of analog, correlation-based, associative, stimulus-response memories, where information is mapped onto the phase orientation of complex numbers operating. It can be considered as a complex valued artificial neural network. The holographic associative memory exhibits some remarkable characteristics. Holographs have been shown to be effective for associative memory tasks, generalization, and pattern recognition with changeable attention. Adaptive resonance theory, Neural Turing machine, One-shot associative memory Hierarchical temporal theory are other variants of the memory network.

D. Other types of Neural Networks

Instantaneously trained neural networks are a type of artificial neural network, which are feed forward artificial neural networks that create a new hidden neuron node for each novel training sample. The weights to this hidden neuron separate out not only this training sample but others that are near it, thus providing generalization. This training can be done in a variety of ways and the most popular network in this family is called the CC4 network where the separation is done using the nearest hyper plane that can be written down instantaneously. These networks use unary coding for an effective representation of the data sets. Spiking neural networks(SNNs) is another class of artificial neural network which fall into the third generation of neural network models, which matches with expanded levels of verisimilitude. Spiking neural network also incorporates time into their operating model. There are other types of networks which doesn't belong to any of the above-mentioned classes including Pulse coded neural networks, cascading neural network, Neuro fuzzy neural networks, Oscillating neural networks, Counter propagating neural networks, Hybridization neural network and Physical neural networks.

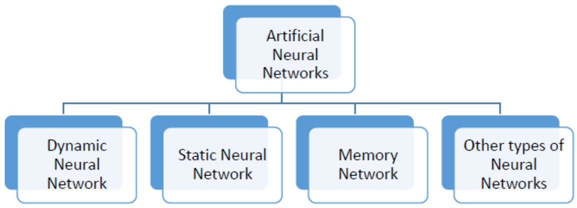

Figure 1: Hierarchy of Artificial Neural Networks

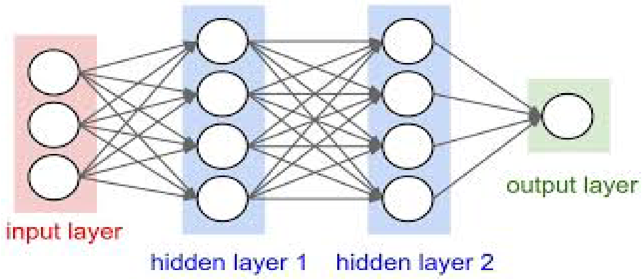

Figure 2: Structure of a Feed-Forward Neural Network with; Image Courtesy: CS231n Convolutional Networks for Visual Recognition, Stanford CS class.

E. Applications of Neural Networks

Neural network has wide range of applications including prediction, classification, recognition, data association, data filtering, and planning. The recognition category cover the range of pattern recognition problems, character recognition or face recognition and processing checks in handwriting. The bomb detection systems in many airports all around the globe make use of the pattern recognition application. Data association function of neural network not only identify the characters that were scanned but also identify when the scanner is not working properly. There will be noise present in telephone signal or other communication channels, neural networks are trained to perform this kind of data filtering tasks excel the existing methods. Planning of unknown environments, can also be solved by equipped neural networks and this used when the sensor data is noisy. The planning methods are new approach to planning. Neural network has its signature in medical industry also. Medical image processing is very healthy field of neural networks and this can be also applied in medical diagnosis. Another emerging method help to identify products in retail outlets with the help of computer vision capabilities.

IV. SEMANTIC SEGMENTATION

Segmentation process partition a digital image into set of pixels or multiple segments and this method is only based on general peculiarity of the image. The objective of this process is to facilitate image into something more relevant or purposeful and accessible to evaluate. Semantic segmentation segregate the image into more meaningful classes than normal segmentation.

Object detection is the process of identifying different instances of the same object and semantic segmentation plays a big leverage when taxing to get the object occurrences. There are number of problems: regions which are not connected may belong to the same object instance and neighboring pixels of the same class might belong to different object instances

A. *Classification of Segmentation Algorithms*

Many segmentation algorithms have published so far by the computer vision associations. These algorithms can be classified if we examine the kind of data that they are dealing with and the type of segmentation they are capable to crop. There are basically four bench marks by which the segmentation algorithms can be restricted.

- Granted classes: Semantic segmentation basically classifies the digital image into different classes so that it is a paramount design choice. Most of the segmentation algorithm know the classes beforehand and these classes will be fixed; some algorithm deals with only two classes like background and foreground [17]. There are segmentation algorithms known as unsupervised segmentation algorithms which do not categorize the classes at all as well as type of algorithms which can classify pixels when they have no knowledge about the class.
- Relationship between the pixels: The relationship between pixels in an image play an important role in classifying the segmentation algorithms. Some algorithms can classify different objects from a single image even if it is not trained for that or the algorithm is not meant to classify the other object. This indicates that simultaneously two or more classes to the coordinates of the image that is being used. There are single class affiliation segmentation algorithms and multiple class affiliation segmentation algorithms [18].
- Type of input data: The data used for segmentation algorithms varies by the application. There are multiple types of data that is being used for the purpose. Basic grey scale images are very common in medical applications such as ultrasonography or magnetic resonance where as some images used for diabetic retinopathy are color images. Robotics and autonomous cars uses depth data as their inputs. Segmentation algorithms can use single images and stereo images [19] as their inputs. The process of finding consistent segmentation for many images are called co-segmentation. The task of segmenting an image is a 2D segmentation task where the tiniest unit is called a pixel. In X-ray CT images [20] the segmentation process becomes 3D and the smallest unit is called a voxel.
- Operating mode of the algorithms: The operating state of the algorithms can be either passive or active. Some among the passive algorithms do segmentation absolutely in automatic manner others work in interactive mode.

B. *Quality Meassures for Evaluation of the Algorithms*

The end users of the segmentation algorithm expect correct results so that evaluation or performance measure is an important part in system integration. There are quality measures which come in picture when we compare segmentation algorithms.

- Accuracy: Accuracy: There are a couple of different ways how this accuracy can be displayed. One way to give readers a first qualitative impression of the obtained segmentations. However, this can only support the explanation of problems or showcase special situation. For meaningful information about the overall accuracy, there are a couple of metrics how accuracy can be defined.
- Speed: When the case of autonomous cars is taken, the speed of the segmentation algorithm is an important factor. Every single image that the system must process should not take more than 20 milliseconds and this is known as latency. Thus, the maximum upper bound on inferencing a single image is a solid requirement in a few applications.
- Stability: The semantic segmentation algorithms should remain stable over small changes in the input image. When the input image is slightly noisy or marginally blurred the output of the algorithms or the segmentation should not vary. The output of the algorithm should be stable with respective to the image perspective.
- Memory usage: The memory usage case matters when the segmentation algorithms are used in smart phones, cameras or when the algorithm should complete the task in a restricted time frame, process the image using a GPU (Graphical processing unit) and deplete so much memory for a single image.

C. *The Segmentation Process*

A classifier which works with a pre-determined set of inputs can be changed to a segmentation engine by adding a sliding window approach [21]. The classifier is trained on an image of immovable size. The classifier which are trained on these fixed size images are then fed with rectangular regions or equally divided sub regions of an image. Although, the image classifier is dealing with a sub image or a rectangular block of pixels, it might only classify the center pixel or subset of the complete window. Neural networks can apply the sliding window approach in a very efficient way by handling a trained network as a convolution and applying the convolution on the complete image.

Figure 3: Output of a Semantic Segmentation; Image courtesy: SegNet- Automated driving system created by University of Cambridge. Computer Vision and Robotics Group/ University of Cambridge.

Traditional Approaches for Semantic Segmentation

The traditional approaches for semantic segmentation do not employ neural networks and they abundantly make use of domain knowledge. The preference of features is super critical in traditional approaches. The commonly used features are color of the pixel, Scale-invariant feature transform(SIFT), Histogram oriented Gradients, Bag-of-visual-words(BOV), Texons [22], Poselets and Dimensionality Reduction. Unsupervised segmentation is another approach and this can never be semantic and these kind of algorithms tries to find consistent regions in an image or region boundaries white semantic algorithm classifies the pixels into different classes. The unsupervised methods include Graph based image segmentation, Active Contour Models,

Random Walks and Watershed Segmentation. Another important class of traditional approach is Random Decision Forests and these apply mechanisms called ensembler learning where multiple classifiers are trained and consolidation of their conjecture is used. An important traditional approach for binary classification task is Support Vector Machines (SVM's) and others include Markov Random Fields and Conditional Random Fields (CRF's).

Post-processing refines a found segmentation and remove evident errors. For example, the morphological operations opening and closing can remove noise. The opening operation is a dilation followed by an erosion and closing operation is an erosion followed by dilation. The opening operation remove tiny segments and closing removes tiny gaps in otherwise filled regions. They were used for biomedical image segmentations

V. NEURAL NETWROKS FOR SEMANTIC SEGMENTATION

Artificial neural networks are classifiers which are inspired by biologic neurons. Every single artificial neuron has some inputs which are weighted and summed up. After the summation, the neural units apply activation function to the weighted sum and gives an output. Those neurons can take either a feature vector as input or the output of other neurons. In this way, they build up feature hierarchies.

The learned parameters are weights of the network and they are learned by gradient descent. To do so, an error function usually cross-entropy or mean squared error is necessary. In the gradient descent algorithm one examine labelled the given training data, the weights of the network as variables and the error function as surface in the weight-space obtained. The minimization of the error function in the weight space of the network acclimate the problem. There are lots of ideas around neural networks like regularization, better optimization algorithms, automatically building up the architectures, design choices for activation functions.

Convolution neural networks are type of neural networks which can learn image filters. There will be millions of parameters to be learned in a training process of a neural network the convolution neural network remarkable reduce the number of parameters which must be learned. The reference to this is given by Alex Krizhevsky et al. in [23]. One major idea for this is called dropout training, which was a clever regularization method. The dropout set the output if neurons while training randomly to zero. Another method is to use the activation function for the network as rectified linear unit or ReLu. These rectified linear units are easier to train than commonly used sigmoid activation function.

After the development of AlexNet a lot of different networks have been developed. One interesting example is, where a recurrent CNN for semantic segmentation is presented. Another notable paper is [24]. The algorithm presented there makes use of a classifying network such as AlexNet, but applies the complete network as an image filter. This way, each pixel gets a probability distribution for each of the trained classes. Semantic segmentation can be done with arbitrary image sizes by taking the most likely classes.

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