Artificial Neural Image Processing Applications: A Survey

Juan A. Ramírez-Quintana, Mario I. Chacon-Murguia and Jose F. Chacon-Hinojos

Abstract— **Artificial Neural Networks (ANNs) have been useful for decades to the development of Image Processing algorithms applied to several different fields, such as science, engineering, industry, security and medicine. This close relationship between ANNs and Image Processing has motivated a study of 160 papers that propose and deal with said algorithms. The information contained in these papers is analyzed, commented and then classified according to its contribution and applications. Then, some important aspects of recent visual cortex-based ANN models are described to finally discuss about the conclusions reached throughout the process.**

Index Terms— **Artificial Neural Networks, Bio-inspired neurons, Image Processing, Computational Intelligence.**

I. Introduction

IMAGE Processing is an area of investigation that uses several techniques and algorithms in order to interpret and understand the information contained in a digital image. Such algorithms may be classified in 6 different types: pre-processing, data compression, segmentation, feature extraction, classification and optimization. For any of these tasks, it is necessary to interpret information with a certain amount of uncertainty associated to it, which is typically done using Computational Intelligence techniques such as Fuzzy Logic (FL), Genetic Algorithms (GA) and Artificial Neural Networks (ANN). The interest on ANNs has been on the rise due to them being inspired on the nervous system, their usefulness for solving pattern recognition problems and their parallel architectures. ANNs have been widely used for Image Processing since the 1950s, when the Perceptron model was first applied to pattern recognition [1]. Ever since, several works have been proposed that make use of ANNs to solve many different Image Processing tasks. Due to the variety of existing works and algorithms, it has been necessary to study and classify their contributions to the area. In 2002 Egmont-Petersen reviewed 200 papers published during the 1990s that discussed many applications of ANNs towards Image Processing. He organized his work according to the taxonomy of the Image Processing algorithms and their levels of abstraction [2]. In 2010 Wang, Ma and Cheng published a review of works related to the Pulse-Coupled Neural Network (PCNN) and its applications on Image Processing [3]. Also in 2010, Misra made a study about the hardware implementations of the ANNs during the last two decades [4]. In 2009 Salhi reviewed various models inspired by the shape and dynamics of Self-Organizing Maps (SOM) [5]. In [6], the Adaptive Resonance Theory (ART) and the SOMs are studied within an analysis of some data grouping methods.

Nevertheless, the analyzed literature does not report reviews about the different types of ANNs applied to Image Processing from recent years. Therefore, this paper tries to address this by reviewing 160 publications from the last 10 years, focusing mainly on the contributions of the different types of ANN architectures to the Image Processing area. From these publications, 138 present ANN-based applications for Image Processing; 16 deal with new ANN models based upon the visual cortex of the brain and 6 analyze ANNs in general. The reviewed articles were selected from several repositories, taking into account the prestige of the chosen publications and congresses and their impact on the Image Processing area. This paper is organized as follows. Section II describes the main ANNs found in the studied literature. Section III discusses the most important applications of ANNs to the Image Processing area, while in Section IV new ANN models based on the visual cortex are analyzed. Finally, Section V shows some results and Section VI discusses the conclusions.

II. Types Of ANNs

After analyzing the aforementioned 138 articles, various ANN topologies were found. The most frequent ones are described below.

Adaptive Resonance Theory (ART)
The basis of this theory is the plasticity-stability dilemma of the learning process. It is implemented using three architectures: ART1 for binary inputs, ART2 for continuous values and gray scale data and ARTMAP, which consists of three modules: ARTa, ARTb and an additional module to observe if the mappings of the input vectors of each class are correct.

Cellular Neural network (CNN)
Based on the Cellular Automata Theory, this type of ANN makes it possible for the neighboring units of the network to interact with each other. Each unit or "cell" is a non-linear dynamic system.

Backpropagation Neural Networks (BPNN)
These are simple Multilayer Perceptron (MLP) networks that use the Backpropagation (BP) learning rule.

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J.A. Ramirez, M.I. Chacon and J.F. Chacon are with the Visual Perception Applications on Robotics Laboratory at Chihuahua Institute of Technology, Ave. Tecnológico 2909 , Chihuahua Chih., C.P. 31310 Mexico. (Phone: +(52) 614-413-7474; fax: +(52) 614-413-5187 e-mail: jaramirez@itchihuahua.edu.mx, mchacon@ieee.org.)

Oscillatory Neural Networks (ONN)
These networks are based on the stimuli with synchronized periodic oscillations that form groups within the visual cortex and may be used to detect features in a certain visual scene. Many different types of ONNs were found in the literature, being the LEGION (Locally Excitatory Globally Inhibitory Oscillator Network) model the most common.

Pulse-Coupled Neural Network (PCNN)
This pulsating network was modeled after the visual cortex of some mammals and is mainly used for pre-processing. It was developed by Eckhom and later modified by Rybak and Johnson. The PCNN consists of a neuron per each pixel of the associated image, and its architecture has three main modules: dendrites, linking and pulse generator.

Probabilistic Neural Networks (PNN)
Consisting of 4 layers, these networks have been inspired by Bayesian Decision Networks. PNNs estimate a Probability Density Function (PDF) to find the class of a vector. On a related topic, another probabilistic model called Gaussian Mixture Model (GMM) was also reported in the literature.

Recurrent Neural Networks (RNN)
This name is given to a type of networks whose internal connections form a direct cycle, such as the Hopfield network, Elman and Jordan's network, the Long Short Time Memory RNN and bidirectional networks. This enables the modeling of dynamic behaviors with the drawback of more memory consumption if compared to direct networks.

Radial Basis Function Neural Network (RBFNN)
These networks typically consist of three layers: the input layer, the hidden layer containing non-linear radial basis functions and the output layer.

Self-Organizing Map (SOM)
A SOM is a non-supervised network based on competitive learning whose architecture consists of a 2-dimensional array. Nowadays, it is widely used on industrial applications.

III. IMAGE PROCESSING USING ANNS

The most common applications found in the literature focus on the following subjects: shape segmentation in medical images (MI), cell and tissue extraction and recognition in biologic images (BI), biometric patterns and gestures extraction (BM), sensing through images in productive processes and remote sensing (SEN), automotive traffic control and security (TR), letters and characters detection (DC), border detection (ES), texture segmentation (TS), color processing (CS), detection of moving objects (MS), shape segmentation methods in general (SS) and other applications (OT).
Each of the analyzed works has been classified according to the category in which it generated the most impact. Figure 1 shows a graph of the resulting number of works for each of the previously described categories. The total number of ANNs does not match with the number of works, since some of them make use of more than one ANN.

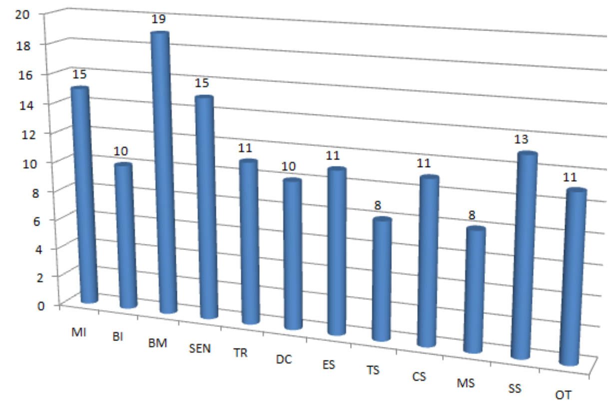

Fig. 1 Amount of ANNs per application.

A. *Medical Image Segmentation (MI)*

This section focuses mainly on MR brain imaging segmentation. These segmentation processes try to split de image into regions that best represent the most important parts for a medical diagnostic. In order to achieve this, several methods such as Fuzzy C-Means (FCM), K-Means, Hopfield networks and SOMs have been used.
The found methods for this type of application are: a PNN-SOM hybrid [7]-[9], RBFNN [10]-[13], the LEGION model [14], RNN [15], SOM [16], CNN [17] and Neurofuzzy [18]. On the first one, a PNN uses a SOM to segment the input, which serves as a reference for estimating the PDFs. These PDFs are then used by the PNN to produce a final segmentation by taking into account the inputs and the reference from the SOM. In [7] and [8] a variation of the PNN, called Weighted PNN (WPNN) is used, and in [9] a Particle Swarm Optimization (PSO) algorithm is used. In [10] a Neurogenetic Algorithm is proposed, where the chromosomes from a Genetic Algorithm (GA) represent a RBFNN that is selected according to the input. In [11] and [12] the authors propose a self-adaptive RBFNN and a Neuro-Fuzzy network with radial activation functions. The work described in [13] uses a RBFNN that is dynamically coupled with a CSAC (Cubic Spline Active Contour) to achieve edge detection on MRI. In [15] the use of a Discrete Time (DTRNN) with Linear Threshold (LT) neurons within a CML (Competitive Layer Model) topology is described, yielding better results than FCM. In [17], a SON-based (Synchronized Oscillatory Network, a similar network to the CNN, but of oscillatory nature) method for biomedical texture segmentation is proposed. Regarding Neuro-Fuzzy systems, the performance of a Neuro-Fuzzy network is compared to a RBFNN and some other Fuzzy methods in [12]; FCM is used jointly with an ANN in [18] and a SOM is used in [16] on images depicting cerebrovascular problems.
From amongst all the proposed methods, Neuro-Fuzzy networks paired with FCM and the PNN-SOM report more performance tests than other methods, showing good results, while also documenting more comparisons against other techniques, contrary to RBFNN-related methods, which only get compared to classic methods such as K-Means and FCM.

B. Biological Image Processing (BI)

This type of application mainly deals with tissue, virus and cell detection. Regarding tissue detection, the studied algorithms first extract important features from an image, which are then used by an ANN to perform a recognition stage, in order to facilitate the visualization of irregularities by an expert. In [19], Chang proposes to use a RBFNN to segment the thyroid gland from a set of frequency features and statistics. The work in [20] aims to detect veins in the retina by means of a BPNN, which classifies pixels as veins or background. In [21] the authors use a SOFM (Self-Organizing Feature Map) to obtain features from the joints of the veins, while in [22] a PNN is used for the same purpose as in [20]. Also, in order to detect anomalies in mammograms, a BPNN [23] and a MCPCNN (Multiple Circular Path Convolutional Neural Network) [24] are used as shape-related feature classifiers, while in [25] a MLP detects suspicious nodules by using contour features. Lastly, in [26] a Convolutional Neural Network is used for image restoration and neural tissue segmentation tasks.

The above tissue recognition methods have been successful from the clinical standpoint, since they accomplish their medical objectives. Nevertheless, except for the vein detection works, the rest cannot be compared with each other, as they have very different goals. With respect to vein detection algorithms, the one from [20] proved to be very effective due to its angle tracking approach, even though it fails in overlapping zones. The method from [21] showed better results than Support Vector Machines (SVM) and K-Nearest Neighbor (KNN).

Regarding the cells and viruses detection, an interesting thing is that they tend to get alligned in a certain orientation to form tissue, which is why Me Lee proposes an algorithm for cancer cells detection via the Hough Transform (HT), while for the feature extraction and the classification the Snake algorithm and a Resource Allocating Network (RAN) are respectively used. The latter is an ANN with a radial activation function, as is described in [27]. In [28], Basak proposes a network inspired by the HT to detect conoidal shapes and tested it on a virus detection algorithm.

C. Biometrical Patterns (BM)

This category is about works related to fingerprint (FP), face (FR) and gesture (GES) recognition and/or detection. For fingerprint detection, it is useful to first segment the image to remove regions that do not contain relevant information regarding the fingerprint pattern and then perform a recognition stage. For the segmentation part, the work in [29] proposes to use a RNN, while the one in [30] suggests a fuzzy algorithm that is used to obtain a threshold which is then used with a Threshold CNN (ThCNN) to group the pixels. Regarding fingerprint detection and recognition, Gour reviews some fingerprint grouping techniques in [31] and [32], from which ART1 ended up being the most effective. In [33] an algorithm that makes use of ART1 and a Modular Neural Network is proposed, and in [34] a Fuzzy ARTMAP (FAM) is used for fingerprint recognition. From these works it is notorious that ART is a very useful technique for the detection and recognition of fingerprints.

Face recognition is a very simple task for humans, yet a very difficult one for machines. Therefore, this area has been receiving a lot of attention, mostly due to its commercial and security-related applications [35], [36]. There are various face recognition methods, from which the holistic, based on the total features of the face and its geometry, stand above the rest. The analyzed algorithms typically comprehend two stages. First, the image is filtered using Kalman, Gabor or Laplacian filters. After that, the feature extraction stage takes place, in which an ANN classifies pixels between face features and background. The literature reported works that use FAM [35],[36], MLP [37], CNN [38] RBFNN [39],[40] and Modular Neural Networks (MNN) [41]-[43]. FAM is used for face recognition in video sequences. For instance, in [36] it is used to detect faces in each video frame while a group of Kalman filters performs the tracking of the regions containing the information of the face. A MLP is used for face detection in [37]; features are extracted with a Discrete Cosine Transform (DCT) to obtain the shapes of the faces. In [39] and [40] Zernike Moments (ZM) are used for feature extraction and a RBFNN for classification; it is important to note that in [40] a Gabor filter is used beforehand to detect the main parts of the face. In [38], CNNs work with a Laplacian-filtered image to achieve face recognition. From amongst these models, the ones using FAM stand out because of their good results: in [35] they achieved a good performance after several tests and in [36] the lowest classification errors were obtained when compared to other methods. On the other hand, the RBFNN method presented in [40] showed good precision in facial expression recognition. The MNN was tested in [41] for face recognition. A multimodal biometric system based on face, fingerprint and speech recognition, using MNN, fuzzy logic and GA was reported in [42] and [43]. The work in [42] presents a comparative study between fuzzy algorithms and MNN, and in [43] an optimization algorithm for the MNN is described.

Regarding Gesture Recognition (GES), an ANN is supposed to analyze points of interest to extract messages by means of anthropomorphic patterns. Many of these patterns are included in the BM category, despite being processed in video sequences, because they focus on pattern detection, rather than moving objects. Tan uses a Restricted Coulomb Energy (RCE) Neural Network to segment hand gestures in images and a RBFNN to recognize said gestures [44]. Nölker and Ritter describe in [45] a method called GREFIT (Gesture Recognition based on FInger Tips), comprised of an ANN that focuses on the angles of the finger joints to recognize gestures. They also use a PSOM (Parametric SOM), which is a set of nonlinear basis manifolds to generate a mapping using topologically ordered reference vectors. In [46] Yang develops an algorithm for gesture recognition by means of a Time Delay Neural Network (TDNN), which uses time windowing on each layer to analyze the signals on the time domain. This ANN searches for point trajectories in video sequences for gesture detection.

D. Sensing through Images (SEN)

This category describes works about product inspection at the process level (PR) and remote sensing (SR). It is very common within the Process Control area to use Image Processing and vision systems to perform quality inspection tasks. Albeit there exists a wide variety of works related to product inspection using vision, the algorithms reviewed for this section have in common that after a pre-processing stage, having obtained a segmentation of the region that represents the product, comes a feature extraction stage in which the features adequately describe the object; afterwards, an ANN is used to classify the objects. Cho developed a Neurogenetic algorithm capable of recognizing flowers, achieving very accurate classification results according to the obtained confusion matrix [47]. Pan proposed an algorithm for the recognition of crops and weed, in which a RBFNN is used for the classification, yielding better results than morphologic methods [48]. Wee uses ZM jointly with a FAM to classify rice grains, resulting in a quicker convergence during training than a BPNN [49]. Hua developed and validated an algorithm for girder recognition by using wavelet decomposition and ART2 [50]. Weitao Li proposes a method to detect burns in industrial processes using Principal Components Analysis (PCA) for feature extraction and three PNNs in order to detect the state of the burn [51]. This method showed better results than classic segmentation methods. According to the authors, the best results for the recognition arise when using the HSV color space. Langner describes an algorithm for object detection in sonar images, in which the segmentation is done using an iterative fuzzy model combined with the Snake algorithm, and a PNN is used for the object classification [52]. Laurentys used a Neuro-Fuzzy Network to diagnose electrical overloads, obtaining a performance of 85% and 90% on the validation tests [53].

Remote sensing is a common thing in various fields of science and engineering. For instance, it is especially useful to sense surfaces by means of an airplane or a satellite. One of the most powerful tools for this type of sensing is the spectroscopy, better known as multi/hyperspectral remote sensing. The literature shows some methods focused to this. To classify regions as land, forest and water, a MLP with weights as Gaussian activation functions (GSBP) is used in [54]; to serve the same purpose, a combination of a BPNN and a SOM is used in [55], while a Mixture Model ARTMAP (ART-MMAP) [56] and an edge-based region segmentation using a CNN [57] and a PCNN [58] are also used. Both GSBP and ART-MMAP yielded good results in terms of the region segmentation, since GSBP had a performance of 88%, while ART-MMAP showed better results than ARTMAP and Regression Tree in error measurements. The CNN yielded good results at enclosing regions compared to classic edge detection methods. Another important application is dust storm detection, for which Rivas uses a PNN and the Maximum Likelihood Classifier (ML), the PNN obtained better results than the ML in this task [59]. Christodoulou and Michaelides propose in [60] an algorithm in which K-Nearest Neighbor (KNN) and a SOFM group pixels into classes of clouds, where SOFM yielded a performance of 61% and KNN of 64%. Finally, Dominguez developed an algorithm to track wastes for NASA, in which a PNN and a Genetic Algorithm (GA) are used to classify regions that are considered anomalous [61].

E. Surveillance Systems and Traffic Control (TR)

Nowadays, it is very common to use cameras and networks in surveillance and traffic control systems [62], [63]. Regarding surveillance systems, Di applies the ART2 to intruder detection [62], while Klima makes use of a BPNN to predict the resulting quality of the images from a surveillance system [63]. With respect to road traffic control, the work [64] proposes an algorithm based on feature extraction using ZM and FAM as a classifier to recognize traffic signs. Wang used the CNN under a statistical domain, assuming each pixel of an image as a Gaussian model and tested it on segmentation of moving automobiles [65].

Regarding road detection, in [66] a BPNN is used to segment shapes from satellite images, while in [67] the LEGION model is used. Also, for the same purpose, in [68] a Tree Structured Belief Network (TSBN) and a MLP are used in rural and urban scenarios.

Several works with different ANNs and statistical models have been used for license plate recognition. License plates could be seen as images with irregular textures or abrupt changes [69]. In order to detect them, one must define a method to detect the Region of Interest (ROI) and another one to detect the characters. In [69] and [70] the ROI is extracted using Sliding Windows and the classification is made with a PNN. In [71] the segmentation of the ROI is achieved by means of HT and histogram analysis, while the recognition uses PCA and a RBFNN. Finally in [72] the Filled Function Method (FFM) is proposed jointly with a BPNN for character detection in license plates. With respect to these methods, the one related to the PNN yields the best results.

F. Character and letter Detection (DC)

One of the most interesting applications of ANNs is letter and text recognition in documents. There exist many types of letters, so the works that focus on character detection differ a lot from each other, not only due to the algorithms themselves, but for the type of letter they are meant to recognize. In the analyzed literature, Farsi, Thai and Latin (uppercase and lowercase) character detectors are reviewed. With respect to ANNs, the RBFNN showed good Farsi and Arabic characters detection [73], [74]; in [73] three RBFNN in cascaded are used, one to detect the signature, another to generate subclasses and a third for detection purposes; in [74], a RBFNN is combined with a GA and K-Means. ART is used to detect letters and characters in [75]-[79], with good results at detecting Farsi characters [76] and letters [77]. A FAM is proposed in [75] to detect Thai characters, while in [76] a simplified FAM makes an optimized classification using PSO. ART1 is applied in [77] to recognize letters, while it is used in [78] to recognize handwritten characters. It is shown in [79] that ART1 is better at grouping text than KNN and Support Vector Machines (SVM). Works from [80] and [81] deal with letter segmentation on hardware, using the LEGION model and a Neuromorphic Oscillatory Network (NON) respectively. A 5-layer Fuzzy Neural Network is applied to texture and text line segmentation in [82]. Within this network, the second layer contains the membership functions, the third comprises a Takagi-Sugeno-Kang inference layer and the fourth contains two output nodes per each of the rules from layer 3.

G. Edge and Contour Detection (ES)

Edge detection consists in obtaining the high-frequency information contained in a digital image. The Image Processing area offers many techniques to achieve this. However, many of said techniques may generate noise or considerable discontinuities on the edges of interest [83], which is why ANNs stand out as an interesting strategy for this. Regarding edge detection with ANNs, the literature describes various works, such as [13] and [84]-[87], in which a RBFNN, a SOFM, a RNN, a Neuro-Fuzzy Network and an Excitable Membrane –a bi-dimensional model of pulsating neurons‒ are respectively used. Also, a CNN is used in [57] and [88]-[94]. The RFBNN used in [13] has already been mentioned in the Medical Imaging subsection. To detect objects using edge information, the work in [80] makes use of a SOFM and the one in [84] a CNN, both yielding good results at enclosing representative regions of the objects from the edges. Regarding contour detection, a Lotka-Volterra Recurring Neural Network (LV RNN) is tested in simulations in [89], and a Discrete Time CNN (DTCNN) is successfully used in various Image Processing applications in [85]. The Neuro-Fuzzy Network and the Excitable Membrane models were successfully validated using various types of scenes [87]. Some CNN variants are proposed in [92]-[94] to solve edge detection problems, reporting a better performance than classic detectors. A hardware implementation of the CNN is proposed in [93] and used for edge segmentation. In [91] the authors use a Fuzzy CNN (FCNN) to detect edges, reporting similar results to classic methods. The most successful varieties were a CNN optimized with a differential evolution algorithm [92] that iteratively achieves dynamic edge detection, and a CNN with two dynamic templates –feedback and control‒ [94], which was tested against an Enhanced Canny algorithm producing better results than the latter on real scenarios.

H. Texture Segmentation (TS)

A texture segmentation algorithm must divide an image into regions with respect to the patterns created by the spatial variations of the intensities of its pixels. In this category, works such as ART2 [95], CNN [17], Random Neural Networks (RaNN) [96], GMM [97], [98], LEGION [99], PCNN [100], SOFM [60], SOM [101] and FAM [102] were studied. The work from [17] has already been studied in the Medical Imaging subsection because it deals with texture segmentation in medical images. In [95] a data grouping algorithm is tested on images containing various texture features with a performance of 78%. In [96] a frequencies and orientations analysis is performed by means of a Gabor filter, further completing the segmentation with a RaNN; the drawback of this method is that it is very time-consuming. Gaussian Mixture Models are proposed in [97] and [98]; in [97] Blekas applies the Spatially Variant Finite Mixture Model (SVFMM) in the segmentation of noisy images, yielding good results but with a higher classification error than the M-Step algorithm; in [98] Mekhalfa uses GMMs to detect defects in soldering with a better performance than FCM. In [99] Gaussian-Markov Random Fields (GMRF) are used to obtain a set of features, while LEGION generates oscillations according to the textures, yielding a better segmentation than non-ANN methods. Chacón and Mendoza propose a texture segmentation method which uses the pulsations of a PCNN to obtain time signatures and evaluate their algorithm with respect to brightness, adjacency and type of texture [100]. As stated in the Sensing through Images subsection, the work from [60] uses a SOFM to detect clouds. In [101] Foresti develops a vision system based on a SOM array that recognizes deformable objects using texture information. In order to do this, two SOMs are used: one for feature extraction and another one for classification purposes; according to the authors, tests showed performances ranging from 82% to 90%. Charalampidis [102] develops a FAMNNm (FAM Neural Network Modification), which is a method for analyzing noise in textures, yielding good results when using images with additive noise.

I. Color Processing (CS)

This category aims to group the methods in which an ANN is used to process color in some way. Various methods regarding this task are reported in the literature, such as ART2 [103], SOM [104]-[108], CNN [109], [110], PNN [111], MLP [112] and a Nonlinear multidimensional scaling method [113]. In [103], ART2 is used to distinguish color in pixels by adjusting the vigilance parameter of the ANN. From amongst the SOM-based applications for color processing, the one in [104] stands out, as it uses a SASOM (Structured Adaptive SOM), which attempts to find an appropriate number of neurons according to the application and classifies colors by means of the competition between neurons. Another variety called SOM-SA, described in [105] combines a SOM with a color segmentation algorithm. In [106] and [107] a SOFM is used for color processing and in [108] a SOTFN-SV, which is a self-organized Sugeno-type fuzzy network, is proposed for color segmentation. A PNN is used in [111] to segment a given color with respect to a previous training, while in [109] a CNN is employed to extract objects in video sequences using color. A layered CNN is used in [110] to segment color under the HSB color scheme. Lastly, a MLP is proposed in [112] to color gray scale images.

The reviewed works show that SASOM and SOTFN-SV are effective to detect skin colors, while a PNN is capable of recognizing a given color in various illumination conditions and the SOFM, SOM-SA and CNN [109] models yield good results for color segmentation on any type of scene.

J. Movement Detection and Mobile Robotics (MS)

This category deals with the segmentation of moving objects in video sequences. The previous subsection mentioned that SASOM [104] and CNN [109] could serve this purpose. Also, in the Biometrical Patterns a TDNN-based algorithm for gesture detection was presented [46]. Now, in [114] a Long Short Term Memory RNN (LSTM RNN) and Markov Chains are used to detect moving people in work meetings. In [115], a Background Neural Network (BNN), which is a variant of the PNN, works as a statistical model of the precedent positions of each pixel within a video sequence. Tang proposes the Fuzzy Clustering Neural Network (FClNN), which is used as a self-organized classifier, for movement segmentation [116]. Its validation is achieved on Chinese video-caption detection. Another strategy is a method called Self-Organizing Background Subtraction (SOBS) that is based on visual attention mechanisms. As its name implies, it is a self-organized algorithm that uses background subtraction in order to minimize noise when detecting movement [117]. The SOBS and BNN models turned out to be useful, as they can be applied to movement detection in many different situations.

Within the Robotics area, it is common to develop mobile robotics applications, which require a movement detection module. In [118] an experimental hybrid model is proposed and tested using a MLP-ART2 simulation focused on mobile navigation. Another navigation model is described in [119]. Said model is based on a Reaction Diffusion CNN (RD CNN) implemented in a FPGA and used in a mobile robot. Also, in [120] a RNN with Parametric Bias is used jointly with a Hierarchical Neural Network to detect objects; this was implemented on a humanoid robot.

K. Shape Segmentation (SS)

This category comprises the algorithms that are capable of interpreting an image and splitting it into regions according to the different shapes and objects, or in other words, performing shape segmentation. Regarding these models, in [121] a Modular ARTMAP (MARTMAP) is proposed, yielding better results for the vigilance parameter than other ARTMAPs. Ravishankar presents a non-supervised network with dynamic units based on Hebbian learning for shape segmentation [122]. Another method for this is the ONN [123], which, according to the literature, showed good results when implemented in hardware. In [124] the LEGION model is used, and in [125] this type of model was used with an associative memory. In [126] and [127] ANNs with chaotic neurons are proposed, while in [128] a Transient Auto-associative Neural Network (TCAN) is used. A CNN is also used for shape detection in [129] and in [130] a CNN model based on polinomial approximations (PoCNN) is proposed for region segmentation. With respect to object detection, in [131] a non-supervised network comprised of a PCA kernel and a RBFNN is proposed, and in [132] Bianchini uses an appearance-based method to detect objects with a RNN. In [133], Le Meur analyzes six different methods and then proposes one to obtain visual salient features and then visual attention of an image. GMM is used to reduce the amount of background pixels when obtaining the salient features.

From amongst the presented works, only Le Meur performs precision tests and compares his method with others. The rest of them show either partial results or simulations.

L. Other applications (OT)

A classic Hopfield network was used for noise elimination in [134]. Regarding hardware implementations, the literature reports the usage of CNNs and ONNs. These methods are implemented in various types of hardware, such as GPUs [93], [135], FPGAs [80], [136], [137] CI CMOS [81], [138] and processing cards [139]. A wavelet, BPNN and ART2-based algorithm for 3-D image mapping is proposed in [140]. Another network used for 3-D reconstruction is the Convolutional Neural Network [141]. The Self-Organizing Tree Map (SOTM) is a SOM-like model similar to ART that is used for multimedia processing [142]. With respect to algorithms, Shiblee uses a variation of MLP in which the aggregation of the weight vectors and the inputs is based on the Generalized Power Mean (GPM) algorithm [143]. In 2010 Rajini published a performance evaluation of algorithms that use BP variations for ANNs applied to object recognition. The studied variations were BP*mom* (momentum variation), *Through Time*, *Resilient* and *Quick*. BP*mom* proved to be the fastest-converging algorithm [144].

IV. Novel ANN Models

The visual cortex is the part of the brain that is dedicated to process the visual information coming from the eyes. As new theories regarding how this part of the brain functions are developed, newer models of artificial neurons and ANNs that could be applied to the Image Processing area have also been created [145]. From amongst the most recent models, we can mention the 2009 analysis by Yotsumoto about how perceptual learning and attention are related. There, the work describes the composition of the visual cortex and its parts –shown on Figure 2–, involved in the process of visual perception [146]. The retina is the first stage in this process, as it captures the image and then transmits it to the optic nerve. From there, the information travels to the lateral geniculate nucleus (LGN) and then to the visual cortex, which is made up of various regions, also shown on Figure 2. Region V1 is the primary visual cortex, V2 is the visual area 2, V4 is the visual area 4 and MT is the medial temporal area. On the upper part of the cortex lies the temporal cortex (TempC) –which is where objects are processed–, along with the parietal cortex (ParC) –where all the spatial information is processed and the attention and decision tasks take place– and the prefrontal cortex (PrFC) –where short-term memory resides and also decision and attention tasks take place–. It can be seen on Figure 2 that each of the areas of the cortex has a feedback and they are all directly related. This means that thanks to the attention process that occurs on the upper part, visual information of a given area can be focused on the bottom part of the visual cortex.

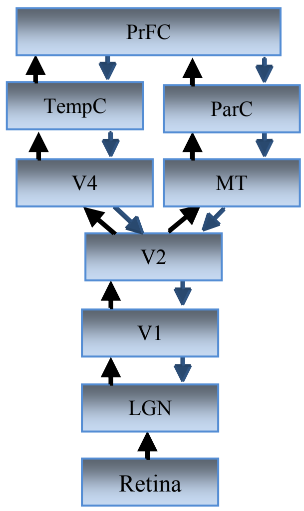

Fig. 2 Parts of the visual cortex [146].

Many works in which computational models based mainly on receptive fields RFs and the primary visual cortex have been proposed. Most of these models use Spiking Neural Networks (SNN). In these networks, the inputs, outputs and sometimes the weights are spikes in the time domain, similar to the action potentials generated by the cells of the nervous system. The PCNN and the ONN could also be considered SNNs. A recent pulsating model is the Comprehensive Bionic Neuron (CBN), which is an artificial neuron that has features from neurons of the nervous system, such as the spatiotemporal sum effect, thresholding features, excitation and inhibition of the cellular membrane, plasticity of synaptic conjunction, delay characteristics, output firing and conducting attenuation characteristics [147]. These terms indicate that the outputs of a CBN are signals that, at any given time, generate a pulsation that results from the space-time aggregation of the inputs. In [148], an artificial neuron model is developed based on a neuron from the V1 area that produces a firing that depends upon a windowed time t, where the input stimulus $s(x,y,t-\tau)$ is associated with the space-time dependent weights $D(x,y,\tau)$ on instant τ as follows:

$$L(t) = \int_0^{\infty}\int D(x,y,\tau)s(x,y,t-\tau)dxdy \qquad (1)$$

where $L(t)$ is the aggregation of the weights with the input stimuli. The weights can be split as:

$$D(x,y,\tau) = D_{sp}(x,y)D_{te}(\tau) \qquad (2)$$

where $D_{sp}(x,y)$ is the effect of the weights in space and $D_{te}(\tau)$ is their effect in time. The output $r_e(t)$ is expressed as a function of the sum of the input stimuli and given by:

$$r_e^i(t) = \sum_{\tau=0}^{N-1}\sum_{y\in\psi}\frac{D_{sp}^i(x,y)}{\left\|D_{sp}^i\right\|}\frac{D_{te}^i(\tau)}{\left\|D_{te}^i\right\|}s(x,y,t-\tau)+I_i(t) \qquad (3)$$

where i is the amount of neurons, N the temporary period, ψ the input area and $I_i(t)$ is the effect of the lateral inhibition [148], so that the aggregated sum of stimuli is actually a space-time relation, that generate a spike train output. This model was tested in a network to detect salient features details in images.

In addition to the analyzed literature, a few aspects regarding SNNs were studied. An interesting one is shown in [149], where the SNN model is used for stereo vision. Here, a six-layer network that incorporates stimuli with temporary features is proposed and serves as a model for stereo perception. A feature of this network is the time used to recognize objects, which is studied in [150], where the plasticity of a visual cortex-based SNN is analyzed. To achieve this, a SNN capable of detecting significant details in faces was developed, and the parameters of the space-dependent plasticity between pulses were analyzed. Also, some works on RF modeling has been proposed like; Gaussian models and receptive filed sets or the LISSOM model, which is a SOM-like model with lateral connections, similar to the visual cortex [151]-[153]. Another topic that has recently attracted interest is the ability to understand the dynamic aspects of pulsating ANNs [154]. An interesting case is Allegreto's, who studied a SNN with impulsive delayed and discontinuous activation functions, from which he concluded that the solution of the network is globally and asymptotically stable [154]. Russell mentions that one of the problems of Spiking Neurons (SN) is that many manual adjustments are required [155]. Therefore, this process is enhanced in his work by proposing an auto-configuration of the parameters.

Besides the SNNs, other models based on dynamic systems that attempt to imitate the behavior of the visual cortex have been proposed, like in [156], where the authors use a model called Parametrically Coupled Logistic Map Network (PCLMN), which involves a network of non-linear dynamic attractors that present a chaotic behavior in order to mimic the primary and secondary visual cortices. In [157], Ulinski mentions that one of the main goals of Neuroscience is to determine the dynamic behavior of neurons, neural networks and how they contribute to the behavior of an animal. In order to do this, he describes a non-autonomous linear differential equation based on the visual cortex of turtles. He used Lyapunov's stability analysis for non-linear autonomous systems and the findings indicate that there exists a fixed stable point at the origin. In [158], Yu proposes an algorithm of neuronal oscillations for visual grouping based on a diffusive connection and a dynamic based on concurrent synchronization, which is tested in various types of segmentation. In [159] continuous attractors modeled from the visual cortex with Linear Threshold (LT) neurons are studied, resulting in a set of LT neuron parameters. In 2009, Brumby implemented a model that stimulates the visual cortex in a supercomputer, based on the mathematical models from Hubel and Wiesel and applied it to remote sensing. Brumby mentions that in order to imitate the visual cortex model in its entirety, calculations of about 1 petaflop are needed [160].

Findings of the models from [148]-[151][156]and [158], show that can be used for segmentation of any shape or object. Therefore, these models may be considered as visual perception models.

V. Statistics and Summary of the Search

A. Summary

This section presents a summary of the reviewed works. Table 1 shows the amount of articles organized by ANN and by application. The PCNN only comprises two works in this table because those were the only ones published after Wang's review [3] in 2010. This review was important for this work because it documents the potential of this type of network and its applications, namely segmentation, pattern and object recognition. As shown in Figure 3, ART was the model with the most results and was proved to be successful in fingerprint, face and character recognition tasks. Regarding the CNN, many works were also proposed. As it was shown in section III, this model has been successful in many applications, excelling in edge and color detection, as well as in hardware applications. Another frequently used model is the SOM, which has been successfully applied to color processing, texture segmentation and movement detection, as well as being useful as a support tool for other networks. PNN is another model that has been successfully applied to MRI segmentation, remote sensing and license plate detection. In other cases, RaNN and GMM have been used for texture segmentation. The RBFNN has been useful on MRI, face detection, Arabic character recognition and cell and tissue analysis. Satisfactory reports on shape and texture segmentation and hardware applications based on ONN are also found in the literature, while the BPNN has been used in tasks related to tissue classification and detection and in TR. Lastly, regarding hardware implementations, the most used models were the ONN and the CNN.

TABLE 1.
SUMMARY OF THE ANALYZED ANNS.

	MI	BI	BM	SEN	TR	DC	ES	TS	CS	MS	SS	OT
ART	0	0	6	3	2	5	0	2	1	1	1	1
BPNN	0	3	1	1	4	0	0	0	1	1	0	2
CNN	1	0	2	1	1	0	7	0	2	1	2	3
ONN	1	0	0	0	1	2	1	1	0	0	5	2
PCNN	0	0	0	0	0	0	0	1	0	0	0	0
PNN	3	1	0	4	2	0	0	3	1	1	1	0
RNN	1	0	1	0	0	0	1	0	0	2	1	1
RBFNN	4	3	3	1	1	2	0	0	0	0	1	0
SOM	4	1	1	2	0	0	1	1	5	2	0	1
Other	1	2	5	2	0	1	1	0	1	0	2	1
Total	15	10	19	14	11	10	11	8	11	8	13	11

B. Types of Processing using ANNs

Figure 4 presents a graph of the different applications of the ANNs found in the literature. They are catalogued according to the type of processing or segmentation done by the network. These categories are described below.

SegF − Segmentation of application-specific shapes. Here lie the works described in the MI category except for [13] and [17]. This category comprises all the works involving digital fingerprint segmentation, letter segmentation, road detection and remote sensing but [54]-[56].

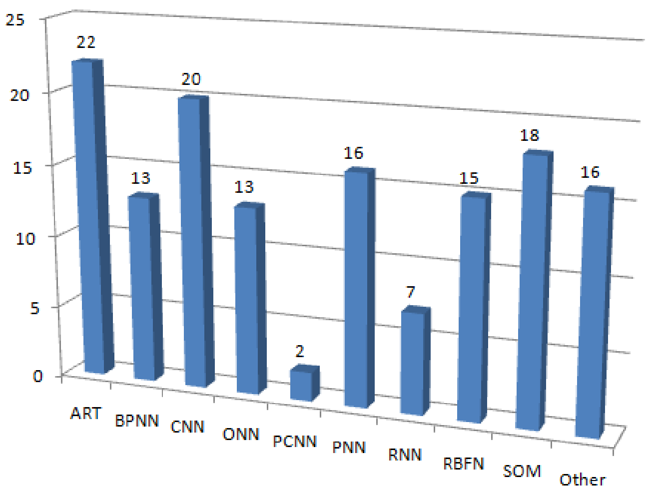

Fig. 3 Amount of ANNs found in the literature by type.

Class − Detection and recognition of objects and patterns. Here, the applications from BI, BM (except fingerprint segmentation) are included, as the ones from PR and TR (except road detection) plus character recognition and OT, without including hardware applications.

Edge − Edge and contour detection, comprising the models described in the ES category.

Tex − Texture segmentation in digital images. Here lie the models from the TS category.

Col − Segmentation and color processing, comprising the models described in the CS category.

Mov − Detection of moving objects. All the works from the MS category that were not part of other categories, except for the ones related to mobile robotics.

SegP – Segmentation for shape and coherent object analysis and interpretation, [148]-[151][156], [158]. Most of the works are based on models that are somehow related to the visual cortex.

HwR – Works related to mobile robotics and Hardware implementations. Also the work from [156] is considered here due to its implementation on an 1144 petaflops supercomputer.

Figure 4 shows recent applications of ANNs. One can observe a marked use in object classification tasks for detection of tissue anomalies, biometrical patterns, industry and security/surveillance. Further on, it can be noted that the networks are used only for segmentation tasks in areas such as MRI, road detection and segmentation of regions in aerial images.
It can also be noted that ANNs were highly used in segmentation algorithms that interpret any information for object detection and non-specific shapes.

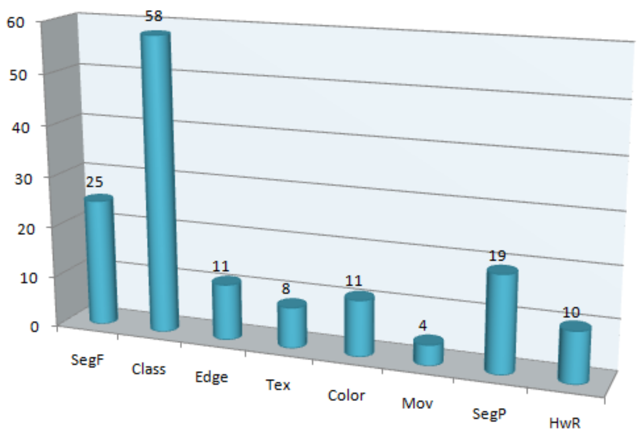

Fig. 4 Different types of processing performed by the ANNs.

VI. CONCLUDING REMARKS

With respect to the 138 reviewed articles, it was observed that the SOM and the CNN models were the most useful for segmentation tasks, as they are flexible enough to be molded into new models for color and edge processing, movement analysis and shape detection. The SOM and CNN models generate stable and consistent results. This makes one think that both models will still be at the cutting edge for years to come. It was also noticed that ANNs are robust enough for medical diagnosis applications because of their capabilities at MRI segmentation and biological tissue detection. However, their usage in the detection of biometric patterns yielded better results.

In regard to monitoring and measurement, ANNs present satisfactory results on classification tasks focused on product inspection, region detection in remote sensing and object detection. Works using ART and PNN report good findings in license plate and character detection.

Most of the models used for shape and object analysis and interpretation are mainly spiking and oscillatory models. Also, the information provided in section IV indicates that most of the SNN models are derived from the current research on the visual cortex. Therefore, it is expected that upcoming ANN models based on findings about the visual cortex may operate in a similar fashion to that of some animal visual system.

Lastly, according to the findings of this work, the trend for the years to come regarding the use of ANNs for image processing tasks will be focused mainly on self-organizing models, CNNs, and pulsating and oscillatory ANNs.

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Juan A. Ramirez-Quintana received the BSc (2004) and the MSc (2007) degrees in electrical engineering from Chihuahua Institute of Technology, Chihuahua Chih, Mexico. From 2008 to 2011 he was a professor at the Chihuahua Institute of Technology. He currently is a Ph.D. student at Chihuahua Institute of Technology.

His research interests include computer vision, image processing, visual perception and computational intelligence.

Mario I. Chacon-Murguia received the BSc(1982) and the MSc.(1985) degrees in electrical engineering from the Chihuahua Institute of Technology, Chihuahua, Chih., Mexico, and the Ph.D.(1998) in electrical engineering from New Mexico State University, Las Cruces NM, USA.

His professional experience includes positions as a Graduate Research and Teaching Assistant at New Mexico State University. He has also developed research projects for several companies. He currently works as a Research Professor at the Chihuahua Institute of Technology, in Chihuahua, Chih., Mexico where he is the director of the DSP & Vision Laboratory and the Visual Perception Applications on Robotics Laboratory. He has published more than 105 works in international and national journals and congresses. His current research includes visual perception, computer vision, image and signal processing using computational intelligence, and pattern recognition.

Dr. Chacon is member of the National Research System in Mexico.

Jose F. Chacon-Hinojos received the BSc(2008) and the MSc(2011) degrees in electronic engineering from the Monterrey Institute of Technology and Higher Education, Chihuahua, Chih., Mexico, and the Chihuahua Institute of Technology, Chihuahua, Chih., Mexico respectively.

He has worked on a research project related to object tracking at the Visual Perception Applications on Robotics Laboratory at the Chihuahua Institute of Technology. He has previously published a paper at the 2011 NAFIPS Conferences at El Paso, TX. His research interests include computer vision, computational intelligence, image processing, object tracking and speech and character recognition.