COLLABORATIVE AGENT LEARNING USING HYBRID NEUROCOMPUTING

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ABSTRACT

This paper investigates the use of a hybrid neurocomputing approach to detect and then recognise images. The first technique creates and trains intelligent agents capable of detecting face images by using a Generalised Regression Neural Network (GRNN). The second technique further refines the search by recognising images from the *detected* data set using a feed forward backpropagation neural network. These two agents make up the 'Detection Agent' and the 'Recognition Agent' in an agent architecture that collaborates with each other to detect and then recognise certain images. The overall agent architecture will operate as an 'Automatic Target Recognition' (ATR) system. The architecture of ATR system is presented in this paper and it is shown how the Detection and Recognition Agents (DRA) fit into the overall system. Experiments and results using the DRA are also presented.

KEYWORDS

Multi-agents, hybrid neurocomputing, collaborative learning, security

1. INTRODUCTION

The concept of software identities that have the ability (or intelligence) to perform some of the tasks that humans perform has great potential for numerous reasons. Firstly, intelligent agents could be used to provide humans suggestions or make decisions for them in response to a query. Secondly, intelligent agents could be deployed in dangerous situations to make decisions on behalf of humans. Lastly, intelligent agents could be utilised to perform tasks that are too difficult for humans such as complex computation or quickly responding to certain stimuli that humans may be too slow for. Such intelligent agents have great potential in many diverse industries ranging from commerce to defence.

Dynamic intelligence is more similar to what humans encounter, i.e. having the ability to adapt to different types of situations. This is mainly a result of humans having the ability to learn and recognise different situations (Filippidis et al., 2000). Likewise software can also be written to adapt, recognise and learn from pervious experiences (Tecuci et al. 2002). Neurocomputing is one such method that employs the process of *learning* to mimic the learning process in humans. In this research study we deployed neural networks to train agents to accomplish certain tasks. The role of the agents developed for the case study will be to operate together as an 'Automatic Target Recognition' (ATR) system which should be able to collaborate with each other to detect the presence of faces within an image (Face database, 2004). Such a technology will exploit the ability of intelligent agents to learn from *previous experiences* (to identify face images) and then combine this knowledge with image processing techniques to extract and identify faces from within a regular image containing other details (Boicu, 2002). This investigation will explore the ability of intelligent agents to learn knowledge and to accomplish a task by collaborating with other agents within the system. In Section 2 we present the architecture of ATR system followed by experiment setup and results in Sections 3 and 4. Some conclusions are also provided towards the end.

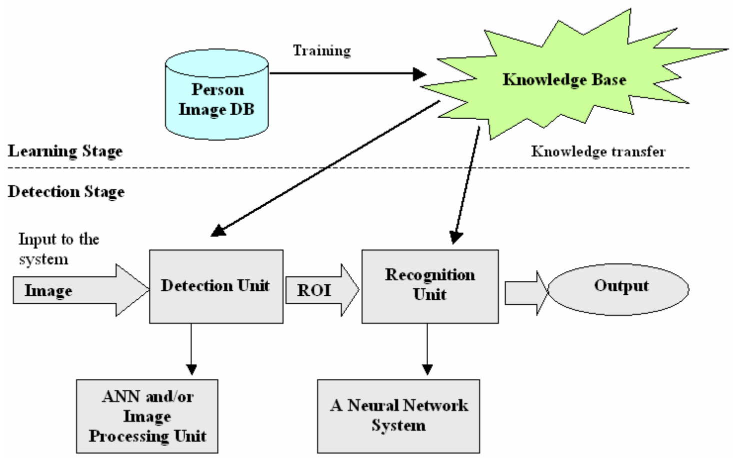

Fig.1. Architecture of ATR

2. ARCHITECTURE OF ATR

It has been suggested that intelligent learning agents could be used in robots for defence purposes. Such robots could be thrown into buildings and then asked to travel though corridors visualising their environment. The aim of these robots would be to seek out objects (i.e. humans, bombs) and inform other robots or humans about knowledge gained. Since the aim of the project is to be able to detect objects (whether it be human, animal or non-living), several different types of sensors could be within the agents. Heat or motion sensors could be embedded into agents to detect the presence of humans and animals. However these sensors may fail if the object is stationary or non-living. Imaging sensors could be a good alternative in such scenarios. A complete and comprehensive intelligent agent could employ all the three sensors (heat, motion and image sensors) to gather information and exchange between other agents to establish certain facts. However for the purpose of this investigation only knowledge gained from imaging sensors is examined.

Before any knowledge can be exchanged between robots an image scanned by a robot must be processed and a decision must be made whether a human is present in the image. This is where intelligence and learning is introduced to these robots. The overall aim of this project is to investigate such a concept. The concept of agents learning from a knowledge base can be tested on an ATR system where agents can automatically detect and recognise images (Farooque et al., 2004). Such an ATR system could be created to investigate collaborative agent learning. Architecture for the development of the ATR system described above could comprise of two different stages: the learning stage and the detection stage. The learning stage would teach an agent what a person looks like. This process would make up the knowledge base for the ATR system. This could be done using ANN and would utilise a series of face images. The entry point into the ATR System would be via the detection stage. This would take images that a robot scans, and tries to detect if there are targets or images of interest within the picture. If possible targets are detected, these images are clipped and a Region of Interest (ROI) is determined. This information is then passed onto the recognition agent. The recognition agent would refine the search and would determine whether the selected images are of the required targets (e.g. people's faces). Once it has been established that a person's face has been detected this information could then be shared between any other robot in the system. The learning stage could be developed as a learning agent that distributes information to the detection stage and the recognition stage. Figure 1 describes how the ATR system would work with the two different stages. The Learning stage comprises of the single learning agent and the detection stage comprises of two types of distinct agents: the detection Agent and the recognition Agent. This agent architecture would operate by having the learning agent constantly training the detection and recognition agents. This would also comprise of constantly updating the database of images for training purposes. The detection and recognition agents would have a single role of detecting possible regions of interest (detection agent) and then recognising specific images from these regions of interest (recognition agent).

2.1. Functioning of Detection Agent

The role of the detection agent is to detect its target image, whether it is of a person's face (Figure 2(a)), a flower (Figure 2(b)) or any other image that the agent wishes to detect. The detection agent is there to simply detect the presence of these target images and pass all the probable candidates to the recognition agent. We modeled the detection agent using a two layer Generalised Regression Neural Network (GRNN). To increase the likelihood of the neural network detecting the target images, the target images are divided into tiles during the training process. The tiles created on the target image form non-overlapping grids, with each region of the grid being made up of binary values of 1 and 0 (since binary images are used). An important factor is determining how many tiles should be used on the image. Too many tiles would result in decreased efficiency due to increased processing time of each tile, and too few tiles would result in the image not being tiled at all. Through experimentation it was discovered that a tiling size of 20 seemed to work best for most instances. The training is then performed on these tiles rather than the target image itself. This ensures a higher success rate if incomplete or distorted images are presented to the network once it has been trained. The number of output neurons for such a network is dependent on the number of target images. Each tile of the target image is assigned the same unique output indicating that it belongs to that particular image. The horizontal rows of pixels in each tile are concatenated to create the network training vector. The first layer has the same number of neurons as there are inputs (for a face image tiled as a 20 x 20 grid, there would be 400 inputs). Each input is then subjected to a weight, derived from the transpose of the input vector of training tiles. When new inputs are detected, the GRNN provides an output, based on interpolation of past records. This is worked out by calculating the difference between the input vector and the training vector, which gives the probability value of each output neuron (Joshi et al., 2002, Seiffert, 2000). The detection of targets (face images) within an image of a room is performed by once again dividing the room image into tiles. These tiles make up the input into the trained GRNN. The output of this GRNN determines the probability of the tiles being targets, and those tiles that may be possible targets are cropped out for further examination. The cropped out tiles become the input of the recognition agent. As a result of the various types of target images that could be possible for the detection agent, no specific physical features in the images are selected during the training and running of the agent. Rather specific imaging features are targets such as number of connected areas present in the image, mean size of the connecting areas, the standard deviation of the areas, all lines higher than the mean length, and the standard deviation of these lines.

2.2. Function of Recognition Agent

Success of the recognition agent is dependent on how well the detection agent has performed. The cropped out images from the detection agent are passed on to the recognition agent as described in the ATR architecture (Figure 1). The recognition agent is trained on the same images used to train the detection agent however this time using a feed forward backpropagation neural network. Presenting cropped out file from the detection agent would add to the overhead of the computation time. The best method would be to present to the recognition agent the five key imaging features extracted from each of the cropped out files in the detection agent. Feedforward neural network is used in the recognition agent for pattern recognition capabilities. During the training, the network is trained to associate outputs with input patterns. When the network is used, it identifies the input pattern and tries to output the associated pattern. In the case of the recognition agent, if the input pattern closely resembles the training data, then the agent will output an identity pattern signifying that a target has been identified. In this case the training set (Figure 2(a) and Figure 2(b)) are used to train the network to correspond to a desired identity matrix [1 0 0 0 0]. As described in Section 2.1 the detection agent extracts specific imaging features as its target. These features are:

1) Number of connected areas present in the image,
2) Mean size of the connecting areas
3) Standard deviation of the areas
4) Lines higher than the mean length
5) Standard deviation of the lines mentioned in (4)

These extracted features from the detection agent are the same imaging features that the recognition agent is trained on. When these extracted features from the detection agent are presented to a trained recognition agent it attempts to match the input with the data extracted from the training image. If a match occurs it implies that the recognition agent has successfully identified one of the extracted images from the detection agent as a positive target. The number of recognition agents that may exist in the overall ATR architecture is variable and is dependent on the number of target images sought after by the system. As shown in section 3, an attempt is made to identify two specific images. Therefore for this system there are two distinct recognition agents assigned to identify the target images.

3. EXPERIMENT SETUP

3.1 Detection Agent - Experimentation using GRNN

As discussed in the Section 2.1, the detection agent is trained using a two layer generalised regression neural network. The agent is trained on target images as illustrated in Figures 2(a-b), which are passed into the system in TIFF format. After training is complete a test image (example: Figure 2(c)) that contains the two target images embedded within a larger image is presented to the trained detection agent. It is now the role of the detection agent to detect possible regions of interests within Figure 2(c). These regions of interests represent regions within Figure 3 where the embedded images may be present. The results obtain from the detection agent (i.e. the images extracted that represent regions of interest from Figure 2 are passed onto the recognition agent to further refine the search and to positively detect and identify the target images. Passing individual images (regions of interest) to the recognition agent may not be very practical as this could possibly greatly hamper the performance of the overall system. A much quicker and effective method that could be used as the input to the recognition agent is to input key features extracted from these regions of interest. The key features from the region of interest that would be extracted from the detection agent are:

1) Number of connected areas present in the image,
2) Mean size of the connecting areas,
3) The standard deviation of the areas,
4) All lines higher than the mean length, and
5) The standard deviation of these lines.

Fig. 2(a) Training image (persons face)

Fig. 2(b) Training image (flower)

Fig. 2 (c) Test image

3.2 Recognition Agent – Experiments Using Feed Forward Neural Networks

As discussed in section 2.2, the recognition agents are trained using a feed-forward neural network. For this experiment the agents are trained on the same training image used to train the detection agent. Before the recognition agent can be trained the same five image features extracted from the cropped out files in the detection agent must also be extracted from the training image. The values of these features may vary vastly between each other. This may lead to the training not meeting its performance goals. For this reason it is important to normalise the values extracted from the image so that they only range between 0 and 1. Once this is done a network can be created and trained. A three layered neural network is created for this experiment where a tan-sigmoid transfer function is used for the hidden layer and a pure linear transfer function is used for the output layer. Training is conducted with the five key image features as the inputs into the network and the identity matrix [1 0 0 0 0] as the target. Once trained the network is ready to have new inputs presented to it. This will allow the network to determine whether the new inputs are target images. At the recognition agent stage the outputs from the detection agent are ready to be presented to the recognition agents. The numerous regions of interests extracted from the detection agent have their features extracted and are then passed onto the recognition agent. The detection agent would yield Nx5 inputs into the recognition agent, where N represents the number of ROIs extracted from the Detection Agent, and 5 represents the five key imaging features extracted. The inputs need to be normalised before they can be presented to the network for the recognition agent. The trained network then examines all N inputs. If the output that results from any of the N images is [1 0 0 0 0] (or closely resembles this identity matrix) then the associated image is a positive target.

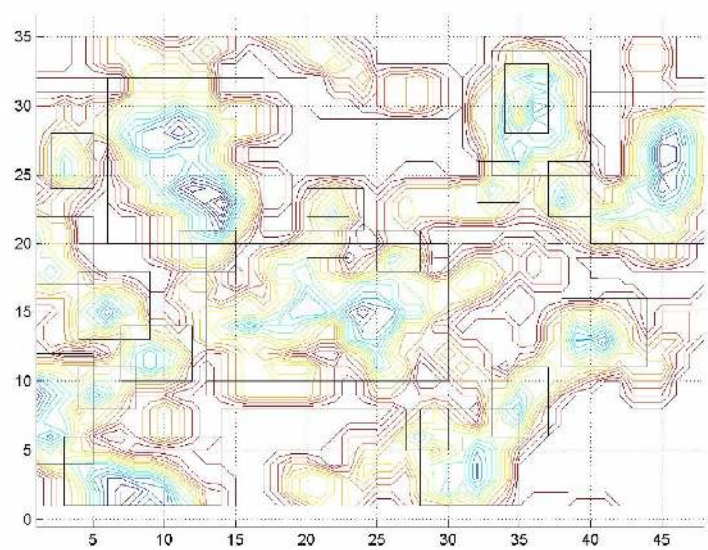

Fig. 3 Contour density plots of ROI

Fig. 4 (a-b) Extracted image clippings

4. EXPERIMENT RESULTS

4.1 Detection Agent

Figure 3 represents the contour density plots of the regions of interest when Figure 2 (c) is passed into the trained Detection Agent. Each contour density plot refers to an area or a ROI on the test image. A filtering mechanism is to be used to extract only those contours that may be probable targets. For this purpose a density threshold level is decided and all contour plots above a set density level are extracted. The extracted ROI look like the figures illustrated in Figures 4 (a-b). These are the clipped images, which acts as the input to the recognition unit.

4. 2 Recognition Agent

The recognition agent is trained using five image features described in Section 3.1. The extracted values for Figure 2 (a) are presented as a training matrix: [10.00,0.08,0.22,18.00,2.26]. These values are normalised so that they range between 0 and 1. A network is developed as described in Section 3.2 and trained against an identity matrix: iIdentity matrix = [1,0,0,0,0]. We used the Conjugate Gradient Algorithm (CGA) with Fletcher-Reeves update. Figure 5 illustrates the learning convergence during the training.

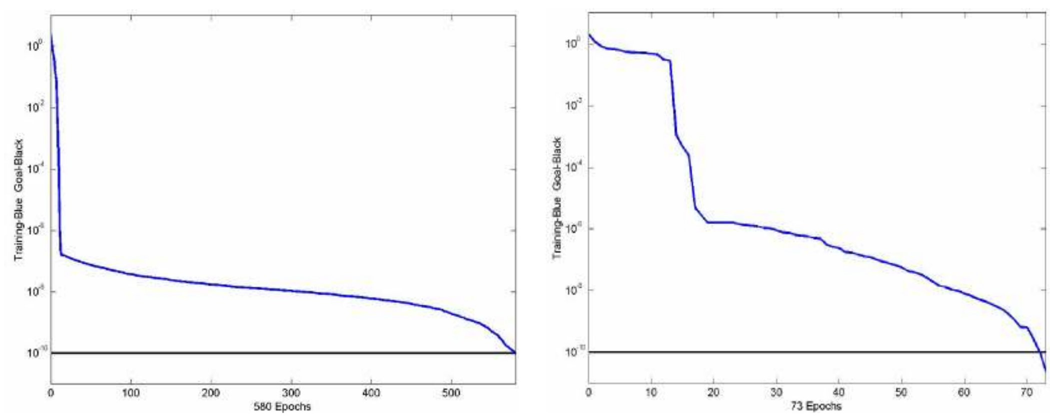

Fig. 5: Learning convergence during training the agents with different target images

ROI number	Matrix	ROI number	Matrix
1	1.52 0 0 0.05 0	12	1.67 0 0 0 0
2	0.25 0 0 0.25 0	13	0.01 0 0 0.01 0
3	0.53 0 0 0 0	14	0 0 0 0.03 0
4	1.64 0 0 0.03 0	15	0.88 0 0 0.08 0
5	0.07 0 0 0.03 0	16	0.22 0 0 0.23 0
6	0.02 0.56 0 0 0	17	0.29 0 0 0.02 0
7	1.64 0 0 0.03 0	18	0.24 0 0 0.24 0
8	0.03 0 0 1.65 0	19	0.18 0 0 0.03 0
9	0.02 0 0 0.01 0	20	0.37 0 0 0.02 0
10	0.02 0 0 0.01 0	21	0.53 0 0 0 0.01
11	0.59 0 0 0.01 0	22	0.06 0 0 0 0

Table 1. Results matrix for target image 1

Once trained, all the ROIs extracted from the detection agent as shown in Figure 3 have their image features presented to the trained recognition agent. For the sample image (Figure 2(c)), 22 ROI were extracted from by the detection agent. As evident, the detection agent was successful in detecting target image and it managed to extract this image as a ROI from the test image. This extracted ROI is shown in Figure 4 (a).

However the success of the recognition agent is determined on whether is can positively identify this target image amongst the 22 other ROI extracted by the detection agent. Table 1 illustrates the 22 rows of the results matrix and each row represents a ROI extracted from the detection agent. The twelfth region of interest extracted (ROI number 12) represents one of the target images. As can be seen in the results matrix, ROI number 12 closely resembles the identity matrix.

As evident from the results matrix for target image, the recognition agent managed to assign four ROI as possible targets. The results shows that ROI 1, 4, 7 and 12 all closely resemble the identity matrix [1 0 0 0 0] and hence are possible target images. However only ROI 12 should have been highlighted as a target, which implies that three false alarm targets were produced. Similarly the training matrix for Figure 2 (b) is extracted as [24.00, 0.01,0.01,26.00,2.47] . 22 ROI were extracted from the test image as depicted in Table 2. This extracted ROI is shown in Figure 4(b). Like before, the 22 rows shown in the results matrix each represent a ROI extracted from the detection agent. The fifteenth ROI represents the next target image. As evident from the results matrix, ROI 15 closely resembles the identity matrix and represents a good result.

ROI number	Matrix	ROI number	Matrix
1	0.67 0 0 -1.07 0	12	0.39 0 0 -1.30 0
2	0.70 0 0 0.70 0	13	0 0 0 -1.20 0
3	0.04 0 0 -1.47 0	14	0 0 0 -1.03 0
4	0.30 0 0 -1.33 0	15	1.05 0 0 0.09 0
5	0.01 0 0 -1.31 0	16	0.59 0 0 0.59 0
6	-1.46 0 0 0 0	17	0.02 0 0 -1.43 0
7	0.30 0 0 -1.33 0	18	0.66 0 0 0.66 0
8	-1.33 0 0 0.32 0	19	0.01 0 0 -1.40 0
9	0 0 0 1.10 0	20	0.02 0 0 -1.44 0
10	0 0 0 -1.18 0	21	0.03 0 0 -1.46 0
11	0.04 0 0 -1.47 0	22	0 0 0 -1.26 0

Table 2. Results matrix for target image 1

5 CONCLUSIONS

The success of the overall ATR System is determined by two main factors:

- The detection agent successfully being able to select ROI from an image that could be possible targets (the images being sort after), and
- The recognition agent being able to refine the results from the detection agent by filtering out extracted ROI that have no relevance and identifying possible targets.

In this paper a detection agent was created and trained to detect different images. A test image containing these images was then presented to the agent and an experiment was conducted to determine whether any positive hits could be achieved. Results from the detection stage of the architecture appear to be quite encouraging. Twenty-two regions of interest were detected and amongst the twenty-two images, the two embedded images were successfully detected. Results from the recognition agent also seem quite encouraging. The detection agent was successful in identifying the targets. However it's the recognition agents role to identify these two images from the twenty-two images extracted from the detection agent stage. To achieve this different recognition agents were developed each trained on a specific image.

Some recognition agent's produced excellent results. But the recognition agent illustrated in the experiment section also produced few false alarms. This recognition agent identified four images that closely resemble the identity matrix [1,0,0,0,0]. This means from the 22 images produced by the detection agent, 18 images could be eliminated. From the four images that this recognition agent identified as possible targets, only one was the intended target image (ROI number 12 from the results matrix). This implies that three false alarms were produced.

The conjugate gradient algorithm used to train the network appears to be the best training algorithm for the recognition agent. Even though some false alarms were detected for test images, when the recognition agent was first trained using different training functions such as the quasi-Newton the false alarms rate was as high as 80%. Another method used to limit the number of false alarms was to reduce the number of ROIs produced from the detection agent. Initially when the detection agent was created a tiling size of 15 was used. This produced close to 40 ROI's, and hence when passed onto the recognition agent increased the likelihood of producing more false alarms. As discussed in Section 2.1 a tiling size of 20 was selected. This seem to work best at a) detecting positive targets within the test image and b) in producing a manageable amount of ROI to be sent on to the recognition Agent. With a tiling size of 20, only 22 ROI were produced as apposed to 40 when the tiling size was 15.

This experiment has shown that an architecture can be created to detect and then recognise target images. The features from detection stage can be sent to the recognition stage where processing is conducted on the initial results to refine and search for target images. By experimenting with the tiling size, the number of ROI's produced from the detection stage can be controlled to produce a number manageable for use in the recognition stage. Also experimenting with the training parameters on the recognition stage, the number of false alarms could be reduced (but not eliminated totally). False alarms were produced on the architecture tested. Eliminating all false alarms may well be an ongoing task in detection and recognition research.

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