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International Baccalaureate

Extended essay cover

Candidates must complete this page and then give this cover and their final version of the extended essay to their supervisor.

Candidate session number	0	0	0	8	6	6	2	2	6
Candidate name	PAUL WOZNIAK								
School number					0	0	0	8	6	6
School name	DARTFORD GRAMMAR SCHOOL								
Examination session (May or November)	MAY	Year	2009						

Diploma Programme subject in which this extended essay is registered: COMPUTER SCIENCE

(For an extended essay in the area of languages, state the language and whether it is group 1 or group 2.)

Title of the extended essay: TO WHAT EXTENT AND EFFECT CAN ARTIFICIAL NEURAL NETWORKS REPRESENT, AND EFFICIENTLY IMITATE BIOLOGICAL NEURAL NETWORKS?

Candidate's declaration

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The extended essay I am submitting is my own work (apart from guidance allowed by the International Baccalaureate).

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Please comment, as appropriate, on the candidate's performance, the context in which the candidate undertook the research for the extended essay, any difficulties encountered and how these were overcome (see page 13 of the extended essay guide). The concluding interview (viva voce) may provide useful information. These comments can help the examiner award a level for criterion K (holistic judgment). Do not comment on any adverse personal circumstances that may have affected the candidate. If the amount of time spent with the candidate was zero, you must explain this, in particular how it was then possible to authenticate the essay as the candidate's own work. You may attach an additional sheet if there is insufficient space here.

PAUL UNDERTOOK THE COMPLETION OF ALL ASPECTS OF THE EXTENDED ESSAY WITH ENTHUSIASM AND CARE. THE RESEARCH PROCESS WAS SENSIBLY SET OUT AND CONTINUALLY MONITORED AND THE ESSAY STRUCTURE WELL PLANNED. PAUL'S PREPARATORY READING WAS COMPREHENSIVE AND THIS IS EVIDENT THROUGHOUT WHAT IS A CAREFULLY CONSIDERED EXTENDED PIECE OF WRITING. APPROPRIATE SOURCES HAVE BEEN SUFFICIENTLY CONSULTED THROUGHOUT AND RELEVANT MATERIAL IS SELECTED.

PAUL HAS DEMONSTRATED A VERY GOOD KNOWLEDGE AND UNDERSTANDING OF THE TOPIC STUDIED & ITS ACADEMIC CONTEXT IS CLEAR. HIS IDEAS ARE PRESENTED IN A LOGICAL & COHERENT MANNER & A CONVINCING & REASONED ARGUMENT IS DEVELOPED THROUGH THE ESSAY.

APPROPRIATE LANGUAGE & TERMINOLOGY FOR THE SUBJECT IS USED WITH CLEAR UNDERSTANDING SHOWN.

THROUGH THE CONCLUDING INTERVIEW PAUL WAS ABLE TO DEMONSTRATE A VERY STRONG UNDERSTANDING OF THE KNOWLEDGE WITHIN THE ESSAY AND EXPLAIN AND DEVELOP ITS CONTENTS.

I have read the final version of the extended essay that will be submitted to the examiner.

To the best of my knowledge, the extended essay is the authentic work of the candidate.

I spent 3 hours with the candidate discussing the progress of the extended essay.

Supervisor's signature: ____________________ Date: 23/01/09

To what extent and effect can artificial neural networks represent and efficiently imitate biological neural networks?

02/07/2008

3933 Words

two vague for a RQ

Abstract

The effective imitation of biological neural networks for the purposes of creating artificial intelligence is becoming increasingly important. This paper concentrates on the current developments in that area. It takes the two types of networks, juxtaposes them and critically assesses the extent to which the objectives of mapping the human brain onto a computer have been achieved. This is done by looking at two major regions: the effect to which the biological neural network has been recreated and the efficiency of this process. To effectively answer the question this paper makes use of a wide range of sources. The artificial neural networks have managed to recreate the structure of the biological neural networks. From the biological point of view the node which represents the neuron does so very well. This provides good basis for future development on the subject. However, the effect is less than satisfactory. The artificial neural networks have proven to us that they can only work efficiently in the simplest environments and when the data is fairly consistent. Hand writing recognition was one of the examples give at which the network gave good results. The conclusions reached here have a number of implications. It becomes clear that achieving artificial intelligence is further then some people might have believed it was. There results found here are only quite general and the paper does not go into very specific areas of artificial neural networks.

which? 2

what question?

scope

conclusions

J => 1

neither the precise area of study, nor the methodology is clear

Contents

(i) *Introduction*

A ≥2

"To what extent and effect can artificial neural networks represent and efficiently imitate biological neural networks?" This research question has been on my mind for some time now and the extended essay allows me to carry out an in-depth investigation to answer it. The reason for my interest in this area comes out of a simple paradox that every computer user comes across even though they might not realise it. When it comes down to mathematics computers outperform humans by far. Computers are excellent at dealing with commands and linear problems that do not require any thought. A good example of this is IBM's new supercomputer named Roadrunner. It can carry out 1.026 quadrillion calculations per second[1]. Now consider this "problem": you are given two pictures, one of a boy and the second of a girl. All you have to do is pick the one with the boy on it. Neither I or you nor a seven-year-old child would have had any difficulty with carrying out that task. A computer would simply fail here. set in context

So why is that? Why is it that computers can instantaneously complete the kind of calculations that would take a life time for a human to carry out and yet they fall short completing a task that we find trivial? What is it that separates us from the machines? Where is the barrier that stops the computers from outperforming us? These are some of the questions that hopefully will be answered through out the course of this essay.

I will start off by presenting the two types of networks and drawing comparisons between them in order to come closer to answering my question. I will be looking at their structure and build. It may be the case that the ANNs (Artificial Neural Networks) show a very similar structure to the ones found in humans and yet they fail to reproduce the effects. That is why I will further look at the efficiency of the ANN at solving problems that do not have known steps to find the solution. This is because if we knew how to arrive at the answer then it would be much more efficient to hard code the instructions and make the computer carry them out.

Another issue that I will address is the one of knowledge, but more precisely where does it come from? How do we learn? This is quite an important question to answer, at least to a certain extent, in order to answer some of the questions stated above. If we go back to the problem of recognising the pictures, how do we know which one shows a boy? Why the computer does not know the answer? Again I am hoping that these questions will be answered as I present my case.

In the increasingly demanding world of today there is a need for automation. Machines and computers play a huge role in our lives today. However in order to satisfy our need to progress and perform tasks faster and more efficiently we require a different kind of assistance. The kind of assistance that no longer would

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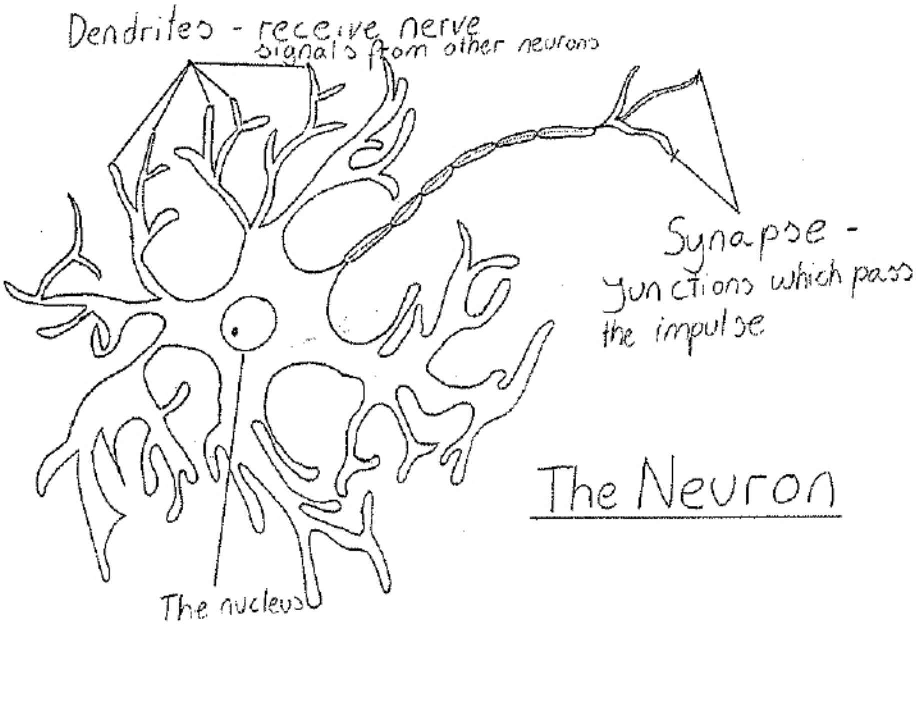
[1] Sharon Gaudin. *IBM's Roadrunner smashes 4-minute mile of supercomputing.* Computerworld. <http://www.computerworld.com/action/article.do?command=viewArticleBasic&taxonomyName=hardware&articleId=9095318&taxonomyId=12&intsrc=kc_top > Accessed on 03/07/2008

need to follow set and rigorous instructions but instead would be able to find its own new ways to overcome the obstacles[2]. Of course what I am talking about here is the artificial intelligence. I believe, as do many computer scientists, that the artificial neural networks are the key in developing machines to the standard that is required today. This is why it is so important to answer my question. To see where we are now and how much are we still lacking.

(ii) Theory behind biological neural networks

In order to appreciate the mechanisms behind the artificial neural networks it is vital to understand how the biological ones work. This is the case because ANNs attempt to imitate then. Straight away this raises an interesting question. How can we recreate something we do not really understand? Is it not quite clear that the ANN will only work to the extent which reflects our current state of knowledge about our nervous system? But what is our current understanding?

Biological neural networks are very complex by their nature. I will break it down into more fundamental parts, which together build up the network, so that it is easier to see and understand. At the lowest and most fundamental level of the network lies the *neuron.* It is outside the scope of this essay to even attempt to describe the complex anatomy and the structure of a neurone, so instead I will explain what role they play in the network.



[2] Pereira, Francisco Câmara. 2006. *Creativity and Artificial Intelligence: A Conceptual Blending Approach, Applications of Cognitive Linguistics.* Amsterdam: Mouton de Gruyter

a. The neuron

Neurons are the "basic building blocks of our brains" [3] and the nervous system as a whole. They are the bricks of a house. Before I continue it is worth pointing out that "there is no such thing as a 'typical' neuron"[4] Each cell, or a group of cells, will be assigned to perform a specific task and it will adopt to that task. Therefore it is quite hard to generalise without leading into misconception. However there are some characteristics that are shared by all neuron cells. Their main function is to pass electrical impulses around the body to our brain so that they may be then processed.

With a lot of simplification the whole process looks like this:

1. The *receptors* in our bodies notice a change
2. The neurons connected to those receptors fire the electrical signal
3. The signal passes from one neurone to another via *synapse*
4. When the brain receives the signal it processes it and send another one back along the neurons to the *effectors*

This is the case most of the time; however when our bodies perform a reflex reaction the signal does not travel to the central nervous system but instead goes to autonomic nervous system where the processing is unconscious[5].

Let me just expand on the pulses of electricity generated by the nerves which are also known as nerve signals. The amount of electricity which is passed along can take many values (within a small range). The voltage value at rest (when no signal is being transmitted) is about -70 millivolts. When the spike occurs this value quickly rises to +40 millivolts[6].With the ranging signal it is quite logical to conclude that it is analogue. Here straight away arises a problem. Computers as we know them work with a digital signal. This is going to have quite a profound effect on the efficiency of a neural network recreated using a machine. Does this mean that we can never truly recreate this type of networks? Not quite, while the Boolean logic is the basis of the computers today there is another logic system called Fuzzy Logic created and developed by one Lotfi Zadeh[7]. It promotes completely different rules that some scientists do not call logic at all.

So when the neurons in our body are connected they form a network. It is an extremely large network with estimated number of neurons in the brain being 100 billion and 100 trillion synapses[8]. If this figure is true, as the research

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[3] Heaton, Jeff. 2005. *Programming Neural Networks in Java*. p. 32.

[4] Arbib, Michael A.2002. *The Handbook of Brain Theory and Neural Networks*. 2nd ed. The MIT Press. p. 3.

[5] Arbib, Michael A.2002. *The Handbook of Brain Theory and Neural Networks*. 2nd ed. The MIT Press. p.399.

[6] *Action potential.* <http://en.wikipedia.org/wiki/Action_potential> Accessed on 04/07/2008

[7] McNeill, Daniel and Freiberger, Paul. 1993. *Fuzzy Logic*. 1st Touchstone Edition.

[8] Williams, R and Herrup, K (2001). *"The Control of Neuron Number."* Originally published in *The Annual Review of Neuroscience 11:423–453 (1988)*. Last revised Sept 28, 2001. <http://www.nervenet.org/papers/NUMBER_REV_1988.html> Accessed on 04/07/2008

suggests, then we come across yet another problem. How can we recreate such a large network efficiently?

Now that we get the picture of the network we must ask ourselves another question. How do we learn? How can we carry out different tasks? This is the point at which a lot of research is still being done and limited information is available. So far the Neurophysiologists (experts in the area of the brain study) believe that the secret lies with in the connections between individual neurons: the synapses.

b. The synapse

The chemical synapse is the most common type of junction. It is thanks to these junctions that neurons can be connected together to form a network. In the computing context they are the key to artificially creating more complicated concepts such as thought and perception. What I am interested is the way in which they pass the *electrical signal* that I have mentioned earlier, from one neuron to another.

Here we come across another fundamental idea: *synaptic strength*. It is this strength that determines whether the signal will be passed along or not. Generally speaking a strong synapse will result in the action potential (the electrical signal) from the presynaptic neuron (the one coming up to the synapse), triggering another signal in the postsynaptic neuron. Logically a weak synapse will fail to do so and that will have the consequence of the signal path stopping at that point. However this is not always the case since within the brain every neuron is connected to many different ones and similarly many are connected to it. So it may happen that a number of weak signals may build up and still cause an action potential to be generated in the postsynaptic neuron.[9]

Often the synapses will gain and lose strength and this is referred to as synaptic plasticity. It is believed that within this ability lies the secret to learning and memory. When strength is gained the synapse becomes "more sensitive to passing on information"[10]. This suggests that we would be more prone to memorising impulses that we have experienced and therefore learn. why? F

As you can see the synapses play quite a vital role in the biological neural networks. When attempting to recreate the learning effect on the machine the key might just be in these highly complex connections. I will now present the

[9] *Synaptic Plasticy.* <http://www.bristol.ac.uk/synaptic/public/plasticity.htm> Accessed on 04/07/2008

[10] Robert Hawkins, PhD. 2007. <http://neuroscienceupdate.cumc.columbia.edu/speakers/speaker_hawkins.html> Accessed on 05/07/2008

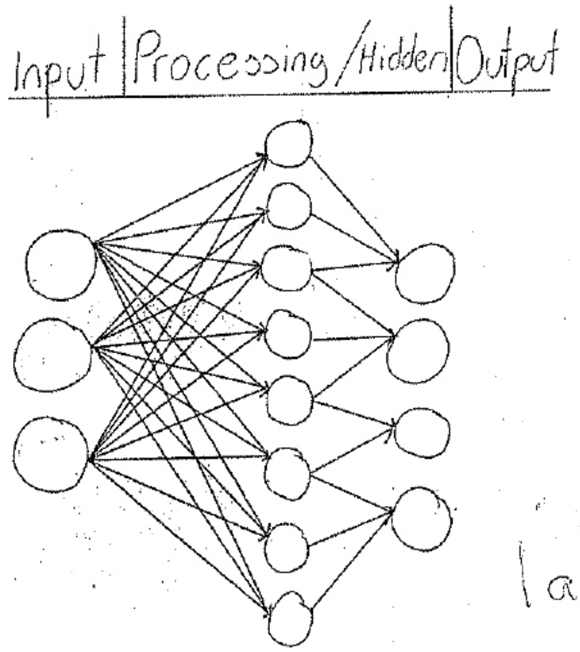
misses the point here that the combined output from different neurons can pass the "threshold" current development in the artificial neural network filed and at the same time assess them in respect to my question.

(iii) Artificial Neural Networks (ANN)

As the name itself suggests they are a recreation of their biological counter parts. The technical term for this is *emulation* as they try to imitate the behaviour and at the same time hoping that the effect will be the same[11]. But is it possible? To what extent have we been able to map our nervous system (and its learning properties) onto a computer? Are there any barriers, such as complexity, that physically stop us from doing so?

So far ANNs have been widely used in character/voice recognition, image analysis and business predictions (stock market)[12]. However, you might think that this is not particularly impressive since our brain has much higher potential. Well, you maybe right. I will now look at different types of neural nets in order to assess if they faithfully imitate the biological networks. It is quite clear to me that if they do not, then it is hardly justifiable to expect the same results on a machine as in our brains.

There are a lot of different types of networks currently in use. However I am only going to talk about the main few which currently shape the way that we perceive the ANNs. Sometimes it is the case that a particular type of network is only an offspring of another one, often inheriting most of its main properties. It will have slightly different features yet the principles will be the same.



[11] Simon Haykin. 1998. *Neural Networks: A Comprehensive Foundation.* 2nd ed. Prentice Hall. p.23

[12] *Applications of neural networks.* <http://cse.stanford.edu/class/sophomore-college/projects-00/neural-networks/Applications/index.html> Accessed on 05/07/08

a. Architecture

As you will find out shortly most of the ANNs have a very similar general architecture. There are three main layers in such a network.

1. The first one will always be the *input* layer. This is logical as you cannot process data while it is absent.
2. Following this is the so called *hidden* layer. This is where the entire processing takes place as the input data is being passed through the net. "The hidden layer is usually about 10% the size of the input layer."[13] Within this layer there can be many more layers. In fact this is completely up to the designer and the requirements of the system that the net is being prepared for. The general rule is that the more layers there are the more complex the net is. This also means that it imitates the biological network more closely.
3. Finally we have the *output* layer which, as the name suggests, returns the output.

Each of these layers consists of artificial neurons which are often called nodes. These nodes, in most cases, will receive the signal from the node preceding it. However, sometimes the level of interconnection is so great that the signal may be passed back or loops around within the hidden layer.

b. The Node

With in the network, nodes represent the neurons and attempt to imitate them. Likewise they will usually have more then one input. This again depends on the purpose of the network and usually does not exceed 100. When all the inputs are taken in they will then be processed and a single output given off. This is called firing.

At the conversion rate of 100 inputs to 1 it makes you think that the net would become incredibly small in a very short space of time. However with in the hidden layer, the individual layers decrease by one node as the signal gets closer to the output. So the number of nodes is in a sense predetermined by the number of outputs that is required.

c. Firing and Weights

The node, our artificial neuron, can fire a signal or stop it from passing forward. In the real neurons this is determined by the synaptic strength. Here however we have so called weights which in principal perform the

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[13] Steven W. Smith, Ph.D. 1997. *The Scientist and Engineer's Guide to Digital Signal Processing.* 1st ed. California Technical Pub. Chapter 26.

same task. So when the input signal is being passed to our current node it is multiplied by the value of the weight[14]. Each of the inputs may be passing through different weights and the output can therefore be different. Once all the inputs are weighted they are summed up within the node. If the value of the sum exceeds the threshold (strength) the node will fire a signal.

example?

d. Feedforeward Neural Network

Perhaps it is most sensible to start off by presenting one of the first neural networks to be modelled. It is one of the simplest networks of its kind and yet it has proved itself to work in certain scenarios. The main feature of this network is that any information that is being passed through it will only travel in one direction[15], hence the name *feedforeward*. This immediately raises an issue about its imitation of the biological network. As I have mentioned earlier the signal in the neurons can travel in both directions. The brain receives as well as sends out signals. However some neurophysiologists will argue that the learning process (after all that is what we are after) does not come from the signals being sent out but from all the impulses that the brain receives.

(iv) Learning

Everything we know, everything we can do, all the actions we can perform and the different ideas we can conjure up were not hard coded into our bodies. All of it is the result of systematic learning that we have done up to now and continue to do so. Allow me to present you with an abstract scenario here. Imagine you are given a task of explaining to a seven-year-old how gravity works. You would not be wrong in thinking straight away that this is going to be a very lengthy process. not true

The simple reason for this is that our learning process is based on a hierarchical model. What it means is that we cannot start at the top and straight away understand a lot of very technical problems. Instead we need to begin with good basis and gradually build on our knowledge until we can solve a certain problem. It is like learning mathematics. Everything that we can do now such as trigonometry and calculus can be traced down to the basic, undeniable ideas called axioms.

The reason I am mentioning this is to show you just as we were not smart straight away, neither can computers be. You cannot expect to build a super

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[14] Nikola K. Kasabov. 1998. *Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering.* 2nd ed. The MIT Press. Chapter 4

[15] Jochen Fröhlich. 2004. *Neural networks with Java: 2004 Edition.* Retrieved from <http://www.nnwj.de/neural-net-types.html> on 05/07/08

complex neural net and see intelligence immediately. It takes time to develop understanding. Of course in the case of machines this process can be significantly shortened as actions such as sleeping and eating will completely omitted. Theoretically a machine could be learning all the time, twenty-four-hours a day. This is an important fact when attempting to recreate the structure and effect of our nervous system.

So how do the machines learn? At the moment a more appropriate name for the process would be "training" as the term "learning" implies building on current knowledge.

a. *Supervised Learning*

This is the simplest and the quickest way of preparing a neural net. When the general structure is achieved and all the nodes are connected in the desired way, the process begins. The net is presented with a set of training data, however it is not expected to process it yet as it does not know how to. This data consists of inputs and desired outputs for those inputs[16]. It is like a matching exercise. The net is shown what inputs go with what outputs.

Let us assume that we are training a net to recognise writing. Typical character recognition you may think. However there are as many different types of writing as there are humans. If we consider ourselves, we were never shown all those types and yet we do a pretty good job at recognising hand writing. Now think of your primary school teacher and remember how they could read anything that the kids gave them even though it made no sense to you. This is because the teacher was exposed to many more types of writing than you. Similarly with neural nets, it needs to be presented with sample data. However in order to be efficient the data is generalised. ?

This brings us to the problem and importance of presenting the net with the right kind of examples. The kind of examples that will allow it to recognise most types of inputs. In other words it needs to be quite generic. Relating this back to the nodes, they are trained to fire when they meet a particular piece of data (or something that looks like it – this is where the error occurs).

this is not particularly clear

[16] Simon Haykin. 1998. *Neural Networks: A Comprehensive Foundation*. 2nd ed. Prentice Hall. Chapter 2

b. Unsupervised Learning

This does not mean that the machine learns completely by itself. It does not start gathering knowledge and building up on it in the sense that we do. The word unsupervised only means unsupervised to a certain extent as there is some user input involved.

It is mostly found to be used with data clusters. In other words data sets. The input can be classified as belonging to a particular set based on its similarity to other inputs within that set[17]. The user determines to what extent the data has to be related in order for it to be placed with in a set.

As much as I love computer science and adore the current paradigms I am going to be very critical here because this is exactly what this particular topic needs. I am going to answer my question three parts. To start off I will determine to what *effect* the neural networks imitate the biological networks.

From the evidence I have gathered neural networks do not come anywhere near to reproducing the effect of the biological networks. If they did then we would be dealing with true examples of artificial intelligence here. However that is far from the case. The program with a neural net implemented is not capable of thinking for its self. It still follows a set of rules, even though they are more complex in their nature. There certainly is a shift from sequential programming towards parallel programming and ANNs provide a gateway for this shift. However at the moment it is no more than that.

I mentioned pattern recognition earlier. When it comes to simple patterns such as hand writing (if we can call it simple) computers have shown us that they are capable of learning to adapt the recognition to an individual after some training. This is certainly a plus in that field and does count towards recreating the effect of the biological networks. However this set will only work in certain conditions. If we begin to write slightly faster where the letters make less of a pattern, yet readable by another human, the computer fails.

This example presents us with a general image of what effect the ANNs have. They work in simple cases however in a little more extreme situation the computer falls short. Furthermore, the character recognition example I presented is a very simple one. If we were to look at object recognition such as a desk, a window or an animal within a picture the computer again falls short. Therefore I must conclude that so far we have only been successful of recreating the effect of the biological neural networks in the simplest scenarios

As to the *representation and imitation* aspect I think we have done a significantly better job than at recreating the design. The ANNs consist of inputs,

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[17] Ben Krose and Patric van der Smagt. 1996. *An introduction to artificial neural networks*. 8th ed. University of Amsterdam. p. 18.

outputs and the process. This is consistent with the receptors and effectors within our nervous system. The structure of the node itself is in principle similar to the neuron. It can have any number of input signals coming in to it and just like the neuron it can either pass the signal forward or stop it at that point within the network.

The concept of the synaptic strength of which we currently understand very little of has been efficiently imitated with the use of weights. I think that for the level of understanding this has been done very well and it represents what happens within the neuron. The weights combined with the summing algorithm and the threshold of the node provides an accurate imitation of the mechanism that operates the neurons. This is exactly the way that the neuron works. So, as for this part I think that the neuron has been emulated very accurately.

(v) Conclusion

In conclusion I want to consider the overall *extent* of the attempt at recreating the nervous system with in a computer. If we agree that the structure of the network has been correctly build and the neuron accurately emulated, why is it that we do not see the kind of processing that we as humans posses. Why is it that the ANNs work only in certain scenarios and many mistakes occur in fields where we would not have much trouble with? I think that the answer lies ironically with in numbers. The networks which have been created are created to a huge scale. The number of neurons in our bodies does not in the slightest compare with our creations. There also is the problem of time. It takes us time to learn different concepts so logically machines would have to take time as well, at least on the model that we are currently working with. I think that as we progress we will see more and more accurate imitations and paradigm shift towards that area of research.

perhaps

opinion not backed up by essay

none of the above has been shown in the main body of the essay

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Assessment form (for examiner use only)

Candidate session number	0	0							

Assessment criteria		Achievement level: First examiner	maximum	Second examiner
	A research question	2	2	
	B introduction	2	2	
	C investigation	3	4	
	D knowledge and understanding	2	4	
	E reasoned argument	2	4	
	F analysis and evaluation	2	4	
	G use of subject language	3	4	
	H conclusion	1	2	
	I formal presentation	3	4	
	J abstract	1	2	
	K holistic judgment	3	4	
	Total out of 36	24		

Name of first examiner: ______________________ Examiner number: __________
(CAPITAL letters)

Name of second examiner: ______________________ Examiner number: __________
(CAPITAL letters)