Emotional System for Military Target Identification

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ABSTRACT

The thought of man-made systems and machines having emotions sounds like science fiction, however, few decades ago the idea of machines with intelligence seemed also like fiction, but today we are developing intelligent machines and using them successfully in different applications. Would we accept the idea of machines that could "feel"? What role would emotions play in machine learning and decision making? How can we model artificial emotions within intelligent systems? Can a machine's decision capability be improved if it had emotions? These are questions one may ask when hearing that machines may have emotions, albeit artificial emotions. In this paper, we discuss these questions, and review briefly some of the latest works on modeling emotions within intelligent systems; including our own model that is based on an emotional neural network (EmNN). The EmNN has emotional neurons, weights, and two embedded emotional responses; anxiety and confidence. These emotional parameters are updated during task learning, and used during decision making. The paper will also present an application of the EmNN to military target identification, in addition to discussing the potential of using the emotional system to improve information exploitation.

1.0 INTRODUCTION

In our daily lives, the amount of information we receive, perceive and then react to is tremendous. Much of our reaction to input information is formed into decisions that we make. What makes us act in a certain way, or decide for, or against an act has its roots back in our previous experiences. Whether we choose anchovies or pineapple on our pizza is a decision we make based on a previous experience with these flavors that leads us to decide what to have. Such a simple process of deciding on our favorite topping is as important and complicated as the more critical decisions we need to make throughout our lives. All decisions involve a learning process, resulting in association, classification and then decision making. During the learning process information which can take different forms, is exchanged between our natural sensors and the main processor; the brain. This sounds very technical and parallel to describing a computing system. However, computing systems lack one aspect of a human processing system; emotions.

Over the past decades machines and systems have been developed and deployed to aid us in decision making and taking action; spanning application areas from simple electronic toys, industry and manufacturing, intelligence and security, to more complicated tasks in medicine, military applications, and space navigation. As the creators (designers) of these machines, we aim to assure that the action or the decision taken by the machine is correct and complies with our way of making a decision. In simplistic terms, we tend to create machines that would make the decisions on our behalf, and as information age progresses, and powerful high-tech systems grow even faster, our expectations of the machines are increasing.

Most of the systems that we develop, and use to make decisions on our behalf, do not go through the learning process and the experiences that we possess. With the exception of some artificial intelligent systems that could interact with their input stimuli, and adapt their output or decision accordingly, systems and machines rely entirely on a set of commands that we provide to govern their actions, and this has been fine until our demands started requiring more complicated decisions by machines. Therefore, more and more intelligent systems are being developed, based in particular on neural networks which form the brain of a machine. These systems imitate our learning process and decision making by repeatedly exposing a neural network to examples of input information and its corresponding output, response, action or decision; this process models the previous experience process in humans. The neural network-based systems have been popularly used, and have shown success in various application areas, where association, classification and decision making can be obtained based on accumulated memory of past experiences.

Despite the success of such intelligent systems, there has been a major and vital difference between a human decision-maker and a machine decision-maker, namely emotion- we have it, and machines do not. The idea of machines with affection or feelings is controversial, and some works expressed doubt about this idea [1,2], however, the concept of machines with emotions has lately attracted the attention of many researchers, and is currently gaining momentum with novel architectures emerging to artificially model emotions in one way or another.

Recent definitions of emotion have either emphasized the external stimuli that trigger emotion, or the internal responses involved in the emotional state, when in fact emotion includes both of those things and much more [3].

The effective role of emotions on cognitive processing, learning and decision making in animals and humans has been emphasized by several researchers [4-8]. Emotions play an important role in human decision-making process, and thus they should be embedded within the reasoning process when we try to model human reactions [9]. Although computers and machines do not have physiologies like humans, information signals and regulatory signals travel within them; there will be functions in an intelligent complex adaptive system, that have to respond to unpredictable, complex information that play the role that emotions play in people [1]. Such computers will have the same emotional functionality, but not the same emotional mechanisms as human emotions. We may think of machine emotions as machine intelligence; we do not expect machines to “feel” the way we feel, but we could simulate machine emotions just as we do machine intelligence [9].

There have been examples of research works that attempted to incorporate emotions in machines in one way or another [9-20]. It was concluded from these works that if emotions such as anxiety, fear, and stress are included in systems that aim to simulate the human behaviour in certain circumstances, the system will be more user-friendly and its responses will be more similar to human behaviour. Other recent research works suggested the use of emotional components within neural models and control systems. For example, Abu Maria and Abu Zitar [21] proposed and implemented a regular and an emotional agent architecture which is supposed to resemble some of the human behaviours. They noticed that artificial emotions can be used in different ways to influence decision-making. Gobbini and Haxby [22] proposed a model for distributed neural systems that participate in the recognition of familiar faces, highlighting that this spatially distributed process involves not only visual areas but also areas that primarily have cognitive and social functions such as person knowledge and emotional responses. Coutinho and Cangelosi [7] suggested the use of modelling techniques to tack into the emotion/cognition paradigm, and presented two possible frameworks that could account for their investigation, one of which explored the emergence of emotion mechanisms. Most of these previous attempts on incorporating emotions in to machine learning have shown successful results, and provided a positive trend to developing machines with emotions, albeit simulated.

Lately, we proposed an emotional neural network (EmNN) which was based on the novel emotional back propagation (EmBP) learning algorithm [23], and used it to solve a facial recognition problem. In other works [24,25], we explored the potential of using emotional neural networks in different tasks, such as more complicated face recognition tasks and in blood cell identification.

The difference between an emotional system and the more traditional approaches; including intelligent systems, is the simulated artificial emotions of the system. These additions have several advantages over traditional approaches.

The embedded artificial emotions narrow the gap between humans and systems; thus instead of "human and machine interaction" we have "human and human-like machine interaction". The closer and more coherent communication of information between humans and emotional systems has the advantage of faster communication, since both systems (human and machine) have emotions. This is not the case with traditional systems, where often a human operator perceives information and makes decisions which could differ due to his/her emotions.

In this paper, we present the emotional neural network (EmNN) and describe its emotional parameters. The EmNN will also be applied to identify potential military targets, such as navy ships, helicopters, jetfighters, tanks and other assorted military vehicles. One of the aims of this work is to mimic the way a human would recognize these targets, by: firstly, using different images of targets with random orientations, angles, and backgrounds, secondly, avoiding complicated image pre-processing phases, and using only global image pattern averaging to simulate a human's "glance" or quick look at a target image, and finally, using the EmNN to perform the target identification, by repeatedly exposing random target images to the network during its training phase; this process simulates the human "getting familiar" with the objects, without the need to look into edges, local features, angles or colors of a potential target.

The paper is organized as follows: Section 2 presents the EmNN and describes the differences between conventional neural networks and emotional neural networks. Section 3 presents the application of the EmNN to military target identification, describing the image database and the EmNN topology. Section 4 describes the implementation results. Finally, Section 5 concludes the work that is presented within this paper and suggests further work.

2.0 EMOTIONAL NEURAL NETWORKS

Neural networks in intelligent systems model the structure and the function of a biological brain, albeit at a much smaller scale. The function of a neural network is to learn to associate certain inputs with already known (to the designers) outputs; this is called training the neural network. Training is completed when the network reaches an acceptable minimum error value, or the number of times (called epochs or iterations) that the network is exposed to the pairs of input/output examples. During training, the memory of a neural network is represented by a set of values, called synaptic weights, which are updated in each training epoch. Once the network learns (completes training) the final values of the synaptic weight are considered the "experience" memory, and are thus used for testing or implementing the trained system. Applications vary from association, to classification, identification and pattern recognition.

When compared to conventional neural networks, the emotional neural network (EmNN) has additional emotional neurons, two emotional parameters (anxiety and confidence), and emotional weights. The emotional parameters are updated during learning, and the final emotional weights are used together with the network's conventional weights to make decisions. The incorporation of the simulated emotionality within a neural network structure aims at further improving the network's learning and decision making capabilities. The EmNN model is based on the emotional back propagation (EmBP) learning algorithm [23]. The additional emotional coefficients (anxiety and confidence) are updated each iteration or epoch during the learning process, and their values are used to update the emotional weights associated with the emotional neurons. Our hypothesis when suggesting such a model for an emotional system is that when we learn a new task, our anxiety level is high, while our confidence is low at the beginning of learning.

Over time, training and with positive feedback, our anxiety level decreases, while our confidence level increases; thus making better decisions in less time.

Figure 1 shows an emotional neural network structure that can be used for pattern recognition and object identification based on presenting the network with input images. There are two emotional neurons feeding the hidden and output layers in the EmNN. These emotional neurons differ from the normal neurons in that they are non-processing neurons which receive global average values of input images, rather than segments or pixel values from that image, also their associated emotional weights are updated using the two emotional coefficients, rather than the conventional learning and momentum rates. In practice, what the two emotional parameters mean is that when the emotional neural network is trained, and as the epochs progress, one term (anxiety level) tells the system to pay less and less attention to the derivative of the error of the training pattern using all nodes as the input average value of the samples of the training pattern, while the other term (confidence level) tells the system to pay more and more attention to the previous change it made to the weights, which is some sort of an increasing inertia term to modify the level of change from one pattern to the next as the training epochs progress.

Full description of the learning algorithm of the emotional neural network can be found in our recent work [23]. However, we describe in this paper the definitions of the two emotional responses which are updated during the machine learning process.

The anxiety level of the EmNN is represented by the anxiety coefficient (μ_i) value, which is defined as:

$$\mu_i = Y_{AvPAT} + E_i \tag{1}$$

where Y_{AvPAT} is the average value of all presented patterns to the EmNN in each iteration; and is defined as:

$$Y_{AvPAT} = \sum_{p=1}^{N} Y_{PAT\_p} \Big/ N \tag{2}$$

where p is pattern index, N is the total number of presented patterns within one epoch, Y_{PAT_p} is the global average value of pattern p. The error feedback E_i in iteration i, is defined as:

$$E_i = \sum_{p=1}^{N} \sum_{j=1}^{N_j} \left(T_{pj} - YJ_{pj}\right)^2 \Big/ N \cdot N_j \tag{3}$$

where j is output neuron index from first to the last neuron N_j, and N is total number of presented patterns p. YJ_j and T_j are the actual and target output value for neuron j, respectively.

The confidence level of the EmNN is represented by the confidence coefficient (k) value which is defined as:

$$k = \mu_0 - \mu_i \tag{4}$$

where (μ_0) is the anxiety coefficient value at the end of the first iteration (a constant value representing the highest anxiety value at the start of new training) and (μ_i) is the anxiety coefficient value at the end of subsequent iteration i (a variable value that is updated each iteration). Anxiety (μ) and confidence (k)

coefficients are dependent on each other; when training starts the initial values of (μ) and (k) are set to 1 and 0, respectively; these values are updated during each iteration using firstly equation (1) to update anxiety value (μ), and then equation (4) to update confidence value (k).

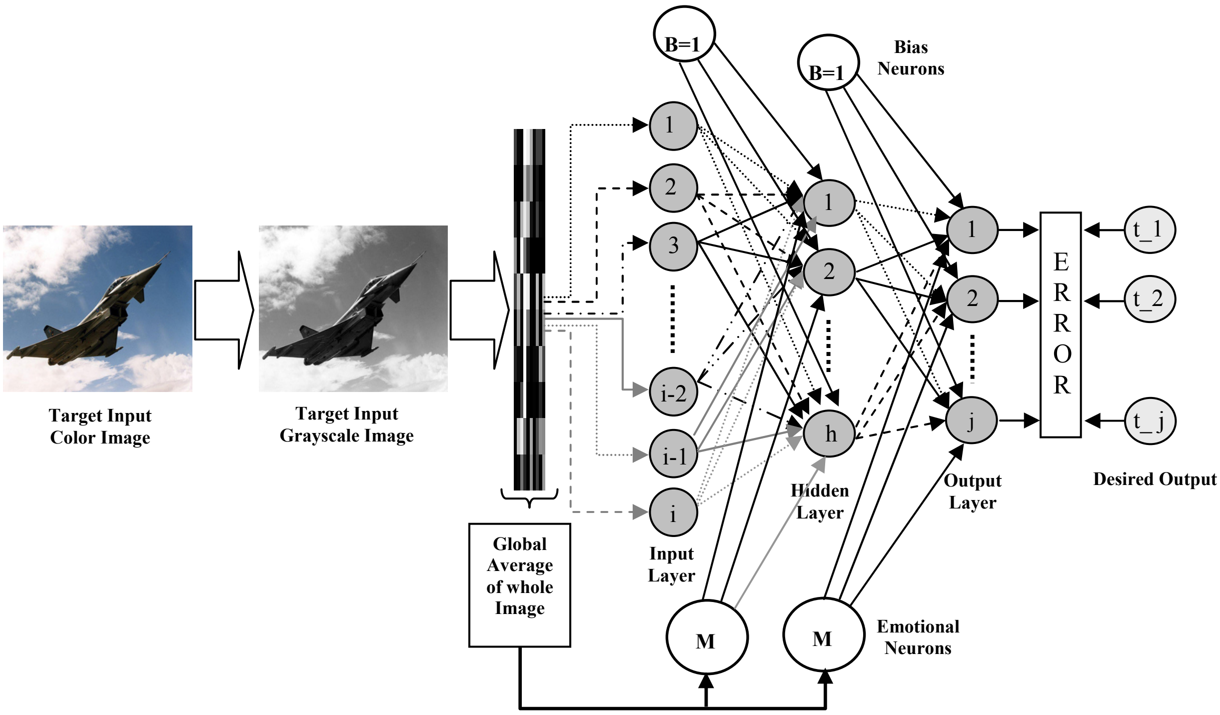

Figure 1: Emotional system and neural network general structure during learning

3.0 APPLICATION TO MILITARY TARGET IDENTIFICATION

In this section, an emotional system based on the emotional neural network (EmNN) is used to identify potential military targets upon presenting their images to the system. In previous works [26,27], we used conventional neural networks, based on the back propagation learning algorithm, in addition to scale space analysis, for military target identification. In this work, we use an emotional neural network in addition to global pattern averaging for military target identification. Global pattern averaging is used for target image preprocessing prior to training or testing the emotional neural network. Averaging is a simple but efficient method that creates "fuzzy" patterns as compared to multiple "crisp" patterns, which provides the emotional neural network with meaningful learning while reducing computational expense. Additionally, global target image identification considers a potential target and its background, which is usually the task performed by a trained human operator who would identify a target; say a boat, regardless of the viewing angle, orientation, distance and background. Our proposed emotional military target identification system mimics the trained human operator's glance at the target using image global pattern averaging, and the operator's recognition or identification of the target using the emotional neural network.

3.1 Military Target Image Database

The implementation of the emotional neural networks uses 100 images of potential military targets. These images comprise 20 images of each of: Navy Ships (labeled and classified by the system as “Boat”), Helicopters (labeled and classified by the system as “Heli”), Jet fighters (labeled and classified by the system as “Jet”), Tanks (labeled and classified by the system as “Tank”), and assorted military vehicles, such as personal carrier, rocket launchers, utility vehicles, and jeeps (labeled and classified by the system as “Vehicle”). Figure 2 shows examples of these images from our database which has been constructed using non-copyrighted images from various open online resources. All targets have random orientations, angles, and backgrounds. All original images are converted to grayscale and resized to 100x100 pixels. The data within these relatively small size images is used for training and testing the emotional neural network.

The method used for presenting the images to the emotional neural network is based on global pattern averaging [24]. A potential target image of size 100x100 pixels is segmented into blocks and the values of the pixels within each block are averaged. The result average values are then used as input data for the emotional neural network. The averaging of the blocks within an image reduces the amount of data required for system implementation thus providing a faster identification system. Global pattern averaging can be defined as follows:

$$PatAv_i = \frac{1}{s_k s_l} \sum_{l=1}^{s_l} \sum_{k=1}^{s_k} p_i(k,l) \tag{5}$$

where k and l are segmented block coordinates in the x and y directions respectively, i is the block number, S_k and S_l are block width and height respectively, $P_i(k,l)$ is pixel value at coordinates k and l in block i, $PatAv_i$ is the average value of pattern in block i, that is presented to emotional neural network input layer neuron i. The number of blocks in each window (of size $X*Y$ pixels) containing a target, as well as the number of neurons in the input layer is i where i = {1, 2,…, n}, and

$$n = \left(\frac{X}{s_k}\right)\left(\frac{Y}{s_l}\right) \tag{6}$$

Block size of 10x10 pixels ($S_k = S_l = 10$) has been used and average values representing the image were obtained, thus resulting in 100 average values in total (n = 100) that are used as the input to the emotional system for both training and testing.

(a) Boat (b) Heli (c) Jet (d) Tank (e) Vehicle

Figure 2: Examples of potential military targets from our database

3.2 Emotional Neural Network Arbitration

The emotional neural network has three layers comprising, input layer, hidden layer and output layer. The input layer has 100 neurons, each receiving an averaged value of the global target image segments. The hidden layer consists of 60 neurons, which was determined after many experiments involving the adjustment of the number of hidden neurons from 1 to 100. The output layer has five neurons according to the number of potential military targets.

The implementation of any neural network consists of training and testing. In this work a total of 100 military target images, corresponding to five potential targets: boats, helicopters, jets, tanks, and vehicles were used. For training the emotional identification system 50 target images were used (10 of each of the target type). The remaining 50 target images were used for testing purposes only and had not been presented to the emotional neural network during training. Figure 3 shows the training target images, whereas Figure 4 shows the testing target images.

4.0 EXPERIMENTAL RESULTS

The experiments that have been carried out, aimed at testing the performance of the emotional neural network in identifying potential military targets. Training and testing the system was implemented using the following system configuration: 2.8 GHz PC with 2 GB of RAM using Windows XP operating system, C-language source code and Borland C++ compiler.

The emotional neural network learnt and converged after 12152 iterations and within 286.2 seconds, whereas the system's running time using one forward pass was (0.00094) seconds, which is the required system by the emotional system to identify a potential target. All 50 training images were correctly recognized when used for testing the trained emotional neural network, yielding 100% correct identification rate. Testing the trained emotional neural network using the remaining 50 target images, which were not exposed to the system before, yielded a correct identification rate of 52%. This rate appears to be low, however, considering the randomness of the target images, in addition to their various lighting, orientation, scale, and types, this result is considered as reasonable, and can be further improved by further training the EmNN using more target images, and larger database. Moreover, our required accuracy rate when identifying a target has been set to a high value, where a minimum error of 0.003 is considered as acceptable. The overall correct identification rate when considering the training and testing images is 76%. Table 1 shows the final training parameters and the correct identification rates for the emotional neural network. If a new target image (not one of the five potential targets) is presented to the trained emotional neural network, then the network classification would be "Unknown Target", and consequently, it is necessary to re-train the network adding the new target image examples to the training image set.

Figure 5 shows the learning curve of the network during training, whereas Figure 6 shows the anxiety and confidence levels during the learning process. The idea of embedding emotional responses and modeling emotions in machines has been motivated by our continuous efforts to create machines that would mimic our functions, learning, and decision making, with a common goal of making machines faster and more reliable. The two emotional responses which are modeled in our work (anxiety and confidence) are both related to the learning and decision making abilities. When inspecting the emotional levels in Figure 6, we can observe the decrease in anxiety level during machine learning, and as learning progresses, while the confidence level increases simultaneously. The emotional system's anxiety level fell from the initial value of 1, to approximately 0.01 at the end of training. Similarly, the confidence level increase from the initial value of 0, to approximately 0.47, which can be actually further increased with more training examples; this would also improve the identification rate of the randomly chosen targets.

Figure 3: Emotional identification system training images

Figure 4: Emotional identification system testing images

Table 1: Emotional neural network final training parameters and correct identification rates.

Input Neurons	100
Hidden Neurons	60
Output Neurons	5
Learning Coefficient (η)	0.006
Momentum Rate (α)	0.8
Minimum Error (e)	0.003
Random Initial Weights Range	-0.45 to +0.45
Anxiety Coefficient (μ)	0.010291
Confidence Coefficient (k)	0.474352
Iterations	12152
Training Time (seconds)[1]	286.2
Generalization Run Time (seconds)[1]	0.00094
Correct Identification Rate (Training set)	100%
Correct Identification Rate (Testing set)	52%
Overall Correct Identification Rate	76%

[1] using a 2.8 GHz PC with 2 GB of RAM, Windows XP OS and Borland C++ compiler

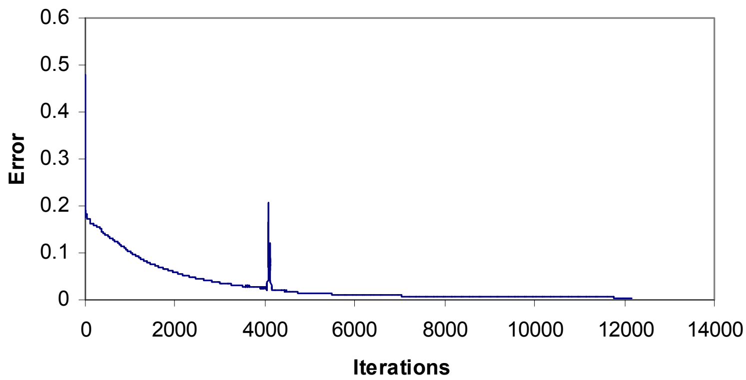

Figure 5: Emotional neural network learning curve during error minimization

The success of the proposed emotional system for military target identification is centred at this stage of developing the system, around the reduction in training time and decision making time. The learning time of the five type of potential military targets, and using random non-uniform target images, is a fast 286 seconds, while the decision making time upon presenting a target image is a remarkable 0.000094 seconds.

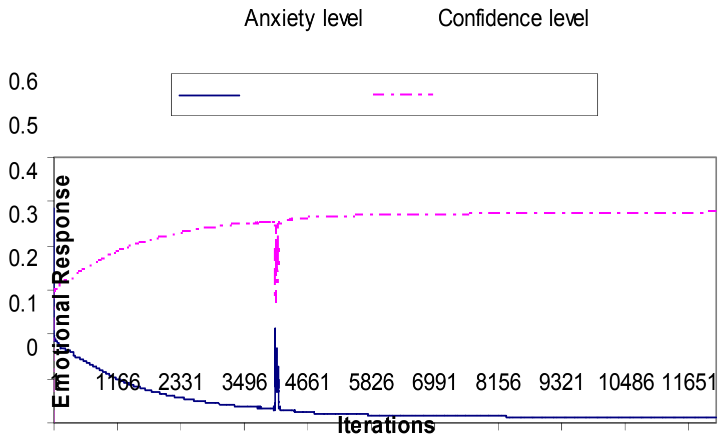

Figure 6: Emotional neural network Anxiety and Confidence levels during learning

5.0 CONCLUSION

This paper presented an emotional system trained to identify potential military targets. The target images comprise navy ships, helicopters, jetfighter, tanks, and other army vehicles. The images, which were chosen randomly, create a challenge for any machine-based identification system; since no image preprocessing in our system is applied to adjust scale, orientation, background, contrast…etc. Instead we aim at mimicking the way a human would recognize such targets regardless of the non-uniformity of the images, and we achieve this by using global representations of the target images. We use an emotional neural network which has within its structure, embedded anxiety and confidence responses that change as learning progresses. Anxiety is high, while confidence is low, at the beginning of learning; this is reversed gradually as learning progresses.

The use of an emotional neural network as the base of our emotional military target identification system, aims also at improving the learning and decision making times and capability of the system. The trained system achieve 100% correct identification when using the training target image set, and 52% using a random non-uniform target image, resulting in an overall rate of 76%. This rate can be further improved, by providing more training images, and using a larger more uniform database. The training time of the emotional system was a fast 286 seconds, whereas the decision making time was a remarkable 0.000094 seconds per target.

The results obtained from our experiments suggest that such an emotional system which has been successfully implemented in other application areas, such as security (facial recognition) and medical (blood cell identification), can be also efficiently used in military target identification, in particular considering the fast performance of the system in terms of training (learning) and decision-making times. Further work, is continuing to improve the identification rate of random target test images, and to establish a large target image database.

While the task of the proposed emotional system focuses on decision making, the system and the novel approach it presents can be further developed to aid effective and efficient management of information in complex heterogeneous systems and from heterogeneous sources. Therefore, the emotional system itself can be potentially used to improve information exploitation.

The incorporation of the emotional features in systems can potentially aid the exchange of information in human-machine environment, as well as improves the learning and decision capability of the machine. Of course, the development of fully emotional systems is yet to come, and scientific work on this novel approach is still in its fancy, however, incorporating such artificial emotions as presented in this work, is the future solution to having better information exploitation, in particular where humans and machines are communicating such emotions.

Further work is being carried on to investigate the modelling of more human emotions in systems and evaluating the effects these additional emotions could have on the systems performance in prediction and classification.

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