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Original Article

A Seq to Seq Machine Translation from Urdu to Chinese

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ABSTRACT

Machine translation (MT) is a subtype of computational linguistics that uses to implement the translation between different natural languages (NL). Simply word to word exchanging on machine translation is not enough to give desire result. Neural machine translation is one of the standard methods of machine learning which make a huge improvement in recent time especially in local and some national languages. However these languages translation are not enough and need to focus on it. In this research we translate Urdu to Chinese language with the help of neural machine translation (NMT) in deep learning methods. First we build a monolingual corpus of Urdu and Chinese languages, after that we train our model using neural machine translation (NMT) and then compare the data-test result to accurate translation with the help of BLEU score method.

Keywords: *Machine Translation; Deep Learning; Neural Machine Translation; Urdu Language; Chinese Language*

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1. Introduction

In the modern globalization era the communication between different countries are more frequent and important than before. So at the same time it's too much difficult to contact in different languages. Around the world there are almost 6500 languages, Language is one of the most powerful tools of any living being to convey their thoughts to the other but it is only possible if the communicating subjects have the same language. A language can be expressed as a series of spoken sounds and words or gestures. It's not possible for someone to learn or speak whole languages. So for this problem, researchers of computer science are interested in developing systems to improve the interaction between humans and computers to make communication possible between different countries[1]. In this field many exports did a lot of efforts on different tool techniques for convey our massage to each other between different languages smokers. In this paper we used Open Neural Machine translation Open (NMT), it is supportive and resourceful way to overcome the barricades in contact in different languages. Neural Machine translation has made great progress nowadays in translation between universal languages such as English and French, English and Chinese etc. However, the number of domestic translation software for non-universal languages is limited[2]. Recently, with the renaissance of deep learning, end-to-end Neural Machine Translation (NMT)[3], has gained incredible performance[4]. Early NMT solutions are typically optimized to maximize the chances of estimation (MLE) of each sentence in the ground accurate translations during the training processing time. However, such an objective cannot guarantee the sufficiency of the generated translations in the NMT model, due to the lack of quantitative measurement for the information transformational completeness from the source side to the target side.

2. Related Works

The Machine interpretation Technique for language interpretation and the other way around had begun extensive back regularly from 1990 onwards. The few techniques and their approaches[5]. According to current investigation, the presentation report of standard frameworks is translating Indian dialects based content (Bengali, Hindi, Malayalam, Punjabi, Tamil, Telugu, Gujarati, and Urdu) into English content with a normal of 10% Rightness for all language pairs[6]. In 2013 Kalchbrenner proposed intermittent persistent interpretation models for machine translation[2]. This model uses a convolution neural system (CNN) to encode a given piece of info content into a solid vector and afterward utilizes a recurrent neural organize (RNN) as a decoder to change over the vector into yield language. In 2014, long momentary memory (LSTM) was brought into NMT[7]. To take care of the issue of creating fixed-length vectors for encoders, they bring consideration component into NMT[3]. The consideration component permits then neural system to pay more thought to the significant pieces of the info, and dispose of in consequential parts. From that point forward, the presentation of the neural machine translation strategy has been essentially improved. In this Sutskever a multi-layer LSTM is utilized to encode input sentence into a fixed-size Bearing and afterward translate it into yield by another LSTM. The utilization of LSTM Proficiently settled the issue of inclination disappearing, which concurs the model to catch information over broadened space in a sentence. Muhammad Bilal utilizes the three order models are utilized for content grouping utilizing Waikato Condition for Information Examination (WEKA). Opinions written in Roman Urdu and English for blog. These suppositions are reports which are utilized for preparing data-set, named models and messaging information. Because of testing these three unique models and the outcomes for each situation are examined. The outcomes show that Gullible Bayesian outflanked Choice Tree and KNN as far as more exactness, accuracy, review and Measure[8]. Mehreen Alam address this troublesome and convert Roman-Urdu to Urdu transliteration into arrangement to grouping learning trouble. The Urdu corpus was make and pass it to neural machine interpretation that theory sentences up to length 10 while accomplishing great BLEU score[9]. Neelam Mukhtar depict Urdu language is poor dialects, for example, Urdu are generally disregarded by the examination network. In the wake of gathering information from numerous web journals of around 14 unique classes, the information is being noted with the assistance of human annotators. Three notable AI calculation Bolster Vector Machine, Choice tree and k-Closest Neighbor (k-NN) which is utilized for test, comparison. Its show that KNN execution is superior to Help Vector Machine and Choice tree as far as exactness, accuracy, review and f-measure[10]. Muhammad Usman additionally portray five notable order strategies on Urdu language corpus. The corpus contains 21769 news reports of seven classes (Business, Diversion, Culture, Well-being, Sports, and Odd). In the wake of preprocessing 93400 highlights are take out from the information to apply AI calculations up to 94% precision[11]. Yang and Dahl their work, first word prepared with a gigantic mono-lingual corpus, at that point the word installing is changed with bilingually in a setting depended DNN Well system. Word catching lexical interpretation data and demonstrating setting data for improve the word arrangement execution. Sadly, the better word arrangement result produced yet can't give critical execution an end-to-end SMT assessment task[12]. To improve the SMT execution straight forwardly Auli upgraded the neural system language model, so as to utilize both the source and target side data. In their work, not just the objective word implanting is utilized as the contribution of the system, yet in addition the present objective word[13]. Liu propose an improver neural system for SMT decoding[14]. Mikolov is right off the bat used to produce the source and target word embeddings, which take a shot at one covered up layer neural system to get an interpretation certainty score[15]. Due to the past inquires about, we convey a training on machine translation from Chinese to Urdu language.

3. Open NMT

Open NMT is an open-source device which dependent on neural machine interpretation framework based upon the Torch/Py-Torch deep learning toolbox. The apparatuses are intended to be easy to understand and effectively open while additionally giving high translation accuracy. This device conveys broadly useful interface, which required just source and target information with speed just as memory enhancements. Open NMT has dynamic open neighborly mechanical just as scholastic commitments. We train our model with the assistance of Open NMT torch/pytorch. There is no work done on Urdu to Chinese language interpretation in past years. We accomplished this work for evacuating challenges in correspondence between these two nations in business just as culture advance line. First we build up an Urdu to Chinese language equal sentences datasets which have in excess of parallel Sentences. From that point forward, we train Our Datasets utilizing open neural machine interpretation (Open NMT) strategy, with customary, measurable machine interpretation.

4. Parallel Corpus

Our dataset consists of 50k Urdu- Chinese parallel corpus which is come from the combination of all the below datasets which are define below.

Monolingual Corpus: which is collected from different Website in which Urdu corpus is around 95.4 5 tokens. These corpus is a combination of quantities such as News, Religion, Blogs, Literature, Science, Education etc.[16].

IPC: The Indic Parallel Corpus is a collection of Wikipedia documents of six Indian sub-continent languages translated into English through crowd sourcing in the Amazon Mechanical Turk (M-Turk) platform[17].

UTCS: Urdu to Chinese Sentence dataset is the collection of different group of sentences from different part of internet[1], news, some from manually hand write because a less parallel Urdu to Chinese sentences present over internet so due to not accessibility of parallel Urdu to Chinese data. We make our own datasets which size is in 50k with the help of taking some part from above datasets and some manually to make our parallel UTCS Dataset for training which is showing in **Table 1**.

Table 1. Urdu to Chinese dataset

Number of Words	Number of Nouns	Number of Verbs	Number of Particles	Punctuation	Number of Sentences
185305	48795	33675	26795	18892	500000

5. Experiment

The several procedures of Open NMT tool are explained in the following subsections.

6. Preprocessing

In this technique the data is passing from preprocessing, which can generate word vocabularies and balance data size, which is used for training.

7. Data Training

We are selecting default Open NMT encoder and decoder, LSTM layers, and RNN. We start our research by using open-source code-base[18]. This code-base is written in Python, using pytorch, an open-source software library. We used two-layer LSTM with outstanding network connections as well as good mechanism to train a translation for our NMT model.

8. Data Translation

In data translation the Open NMT model using binary translation method for creating an output translation file which come from source and target language datasets.

9. Results and Discussions

In Open NMT model we are trained Urdu to Chinese language dataset which is 50k parallel corpus. The validation part of a source and target which have been taken as 20% of training corpus, then for testing the model we have taken 10k sentences randomly from the corpus then we make 7 different test in our model. We selected different result for each data-test and given name UCT and also compare the translation with manually as well as in translation model. We also calculated the BLEU score for every UCT. The details of the each data-test below in **Figure 1** and **Table 2**.

Table 2. UCT result represented with BLEU score

Data-test	BLEU Score	System Information
UCT 1	0.0678	CPU@ 2.70 GHz, Intel (R) core (TM) I7-5700
UCT 2	0.0847	
UCT 3	0.1089	
UCT 4	0.1929	
UCT 5	0.2187	
UCT 6	0.3856	
UCT 7	0.4287	

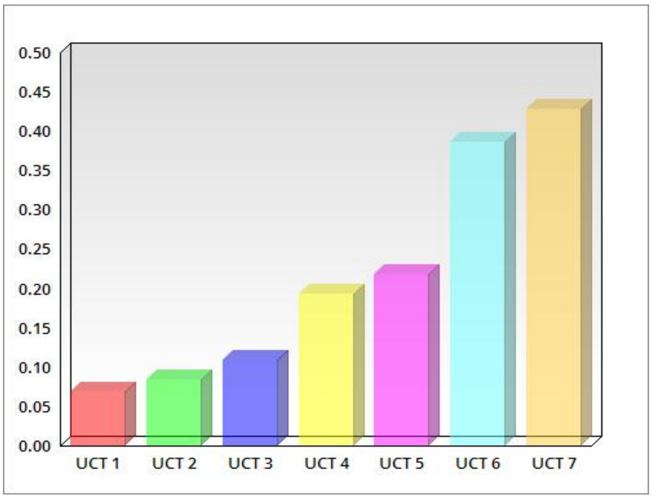

Figure 1. Bar representation of BLEU score of different UCT.

10. Conclusions

We have taken training data from several sources, which is to be made up of different variety of sentences. The training part of our method is done in the shape of UCT, and it has been practical that the BLEU score increases with the number of UCT; accuracy of the system obtained after seven number of UCT which is proper matched to other machine translation systems. We are still trying to improve the BLEU score of Urdu to Chinese translation system by applying some more techniques which are used for generating the best model of translation.

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Original Research Article

Machine Learning, Deep Learning and Implementation Language in Geological Field

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ABSTRACT

Geological big data is growing exponentially. Only by developing intelligent data processing methods can we catch up with the extraordinary growth of big data. Machine learning is the core of artificial intelligence and the fundamental way to make computers intelligent. Machine learning has become the frontier hotspot of geological big data research. It will make geological big data winged and change geology. Machine learning is a training process of model derived from data, and it eventually gives a decision oriented to a certain performance measurement. Deep learning is an important subclass of machine learning research. It learns more useful features by building machine learning models with many hidden layers and massive training data, so as to improve the accuracy of classification or prediction at last. Convolutional neural network algorithm is one of the most commonly used deep learning algorithms. It is widely used in image recognition and speech analysis. Python language plays an increasingly important role in the field of science. Scikit-Learn is a bank related to machine learning, which provides algorithms such as data preprocessing, classification, regression, clustering, prediction and model analysis. Keras is a deep learning bank based on Theano/Tensorflow, which can be applied to build a simple artificial neural network.

Keywords: *Geological Big Data; Machine Learning; Deep Learning; Artificial Neural Network; Intelligent Geology; Python*

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1. Introduction

Geological big data is growing exponentially. They are largely produced in the investigation, exploration and corresponding geological scientific research of basic geology, mineral geology, hydrogeology, engineering geology, environmental geology and disaster geology, the development and utilization of energy and minerals, the monitoring and prevention of environmental and geological disasters, and various space-based and space-based remote sensing observation activities. The ways to obtain geological big data include geophysics, geochemistry, drilling exploration wells, remote sensing and telemetry, sensing monitoring, and they can also come from various expanded applications, such as map compilation, analysis and calculation, simulation, prediction and evaluation, intelligent management and control etc. Geological big data can be structured, such as data obtained from geochemical analysis and geophysical exploration. There are more unstructured and semi-structured data, such as paleontology, minerals, rocks, ore deposits, core photos, tsunami audio, seismic video, structure, remote sensing spectral maps, specimens, field records, geological charts etc.

In this context, any individual handling geological big data in a traditional way is just like a person racing against a car, plane and rocket. The farther he goes, the greater the gap, and finally he is abandoned by advanced means of transportation. Only by developing intelligent data processing methods can we catch up with the extraordinary growth of big data. Therefore, it can be said that artificial intelligence geology should be an important development direction.

Machine learning is considered to be the core of artificial intelligence and the fundamental way to make computers intelligent. At present, the universal view of various basic problems of machine learning and artificial intelligence is forming (**Figure 1**).

Although scientists with a sense of historical mission are exploring seriously and diligently (Mayer-Schonberger & Cukier, 2013; Carranza & Laborte, 2015; de Mulder *et al.*, *2016;* Aryafar and Moeini, 2017; Ross *et al.*, 2018), artificial intelligence geology based on big data is far from mature (Zhang & Zhou, 2017; Zhou *et al.*, 2018a).

As a big data album, this issue focuses on the modeling and application of machine learning (including deep learning) (Xu, 2018; Zhou, 2018; Han *et al.*, 2018; Jiao *et al.*, 2018; Liu *et al.*, 2018; Wang *et al.*, 2018). It also reflects that machine learning has become one of the important hotspots of current geological big data research. The author believes that machine learning will make geological big data winged, effectively process massive data, mine valuable and rich information behind them, and change geology accordingly.

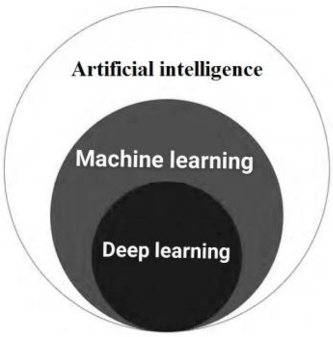

Figure 1. Relationship between artificial intelligence,machine learning and deep learning

2. Classification of Machine Learning

In essence, machine learning is a training process of model derived from data, and eventually gives a decision oriented to a certain performance measurement. Machine learning can be divided into Supervised Learning and Unsupervised Learning. Under supervised learning, each group of training data has an identification value or result value. When establishing the prediction model, Supervised Learning establishes a learning process, compares the prediction results with the actual results of training data, and constantly adjusts the prediction model until the prediction results of the model reach the expected accuracy. The common methods of Supervised Learning are shown in **Figure 2**. In Unsupervised Learning, the data is not specially identified, and the learning model is to infer some internal structures of the data. Common Unsupervised Learning methods are shown in **Figure 3**. In machine learning, SVM (Support Vector Machine) is a representative method. It is based on binary classification algorithm, and its core of thinking is ascending dimension and linearization. Many sample sets that cannot be processed linearly in low-dimensional sample space can be linearly divided (or regressed) through a linear hyperplane in high-dimensional feature space. SVM maps the sample space into a high-dimensional feature space through a nonlinear mapping P, so that the nonlinear separable problem in the original sample space is transformed into a linear separable problem in the feature space.

3. Deep Learning

Deep learning is a subclass of machine learning research. Its purpose is to establish and simulate the neural network of human brain for analysis and learning, and simulate the mechanism of human brain to interpret data, such as image, sound and text. The essence of deep learning is to learn more useful features by building machine learning models with many hidden layers and massive training data, so as to finally improve the accuracy of classification or prediction (Hinton *et al.*, 2006, 2012; Brenden *et al.*,2015; Lecun *et* al., 2015; schmidhuber, 2015; Bianco *et al.*, 2017) “Depth model” is the means and "feature learning" is the purpose.

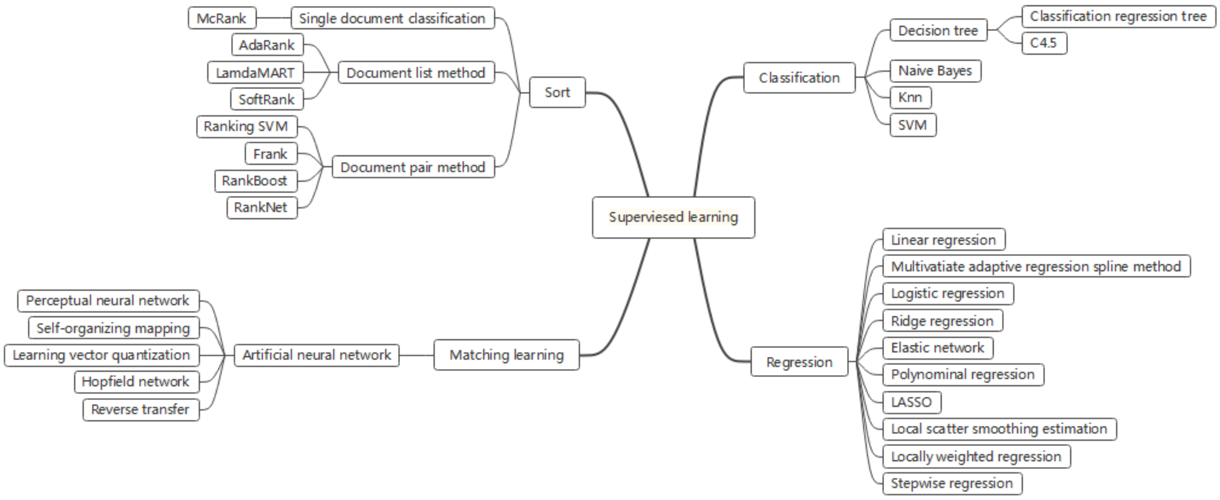

Figure 2. Common supervised learning algorithms (Zhou *et al.*, 2018b).

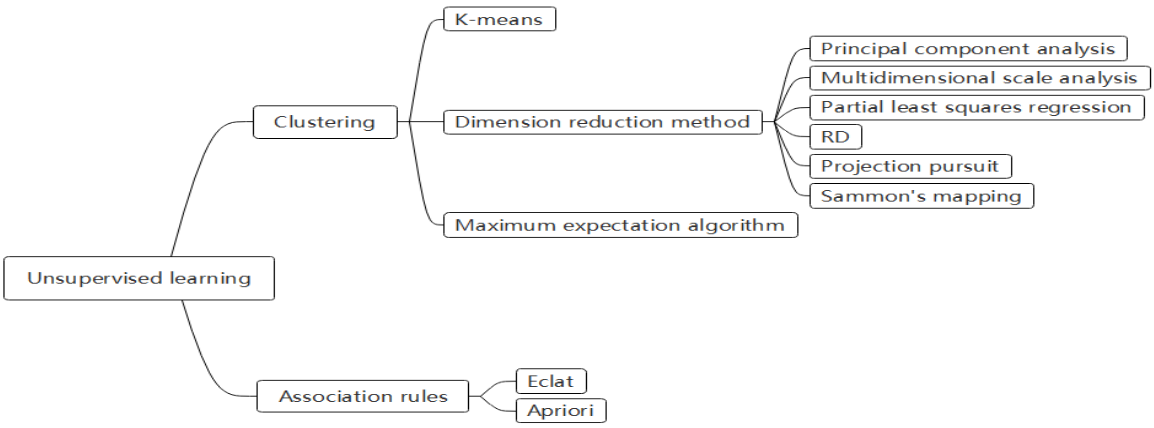

Figure 3. Common unsupervised learning algorithms.

Table 1 Lists the current common deep learning models or methods. Among them, convolutional neural network algorithm is the most commonly used deep learning algorithm. It is widely used in image recognition and speech analysis. It is essentially an input-output mapping, which can learn a large number of mapping relationships between input and output without any accurate mathematical expression between input and output. As long as the convolution network is trained with a known mode, the network has the mapping ability between input and output pairs. Convolutional neural network is a multi-layer neural network, each layer consists of multiple two-dimensional neural networks.

Table 1. Common deep learning models and algorithms

Common models or methods	Algorithm description
Autoencoder	An unsupervised neural network model. The implicit features (ENCODING) of the input data can be learned, and the original input data can be reconstructed (DECODED) with the learned new features. Automatic coders are used for dimension reduction or feature learning.
Sparse coding	An unsupervised learning method. It is used to find a set of "super complete" basis vectors to represent the sample data more efficiently. The method has spatial locality, directionality and band-pass in frequency domain. It is an adaptive image statistical method.

Table continued.

Restricted Boltzmann Machines	RBM, a randomly generated neural network that can learn probability distribution from input data set Restricted Boltzmann machine has been applied in dimension reduction, classification, collaborative filtering, feature learning and topic modelling. According to different tasks, the restricted Boltzmann machine can be trained by supervised learning or unsupervised learning.
Deep beliefnetworks	Dbns, a probability generation model composed of multiple restricted Boltzmann machine layers Compared with the neural network of traditional discriminant model, generative model is to establish a joint distribution between observation data and labels. It can be extended to convolution dbns (CDBNS).
Convolutional neural network	CNN is a kind of artificial neural network. Its weight sharing network structure makes it more similar to biological neural network, which reduces the complexity of network model and the number of weights cnns has become a research hotspot in the field of speech analysis and image recognition.

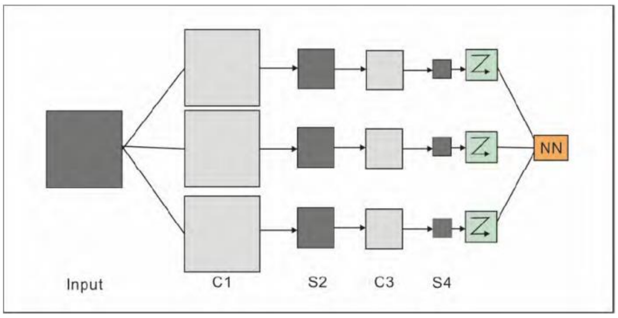

Figure 4. Conceptual diagram of convolution neural network.

Each plane is composed of multiple independent neurons (**Figure 4**). Convolution network is a multi-layer perceptron specially designed to recognize two-dimensional shapes. This network structure is highly invariant to translation, scaling, tilt or other forms of deformation. In this paper, Xu Shuteng and Zhou Yongzhang (2018) took pyrite, chalcopyrite, galena, sphalerite and other sulfide minerals from Jiapigou gold mine in Jilin Province and Shihu gold mine in Hebei Province as examples to design a targeted Unet convolution neural network model to realize the automatic recognition and classification of ore minerals under the microscope based on deep learning algorithm. The experiment shows that the recognition success rate of the trained model for the ore mineral photos under the microscope of the test set is higher than 90%, indicating that the model established in the experiment has good image feature extraction ability and can complete the task of intelligent recognition of ore minerals under the microscope.

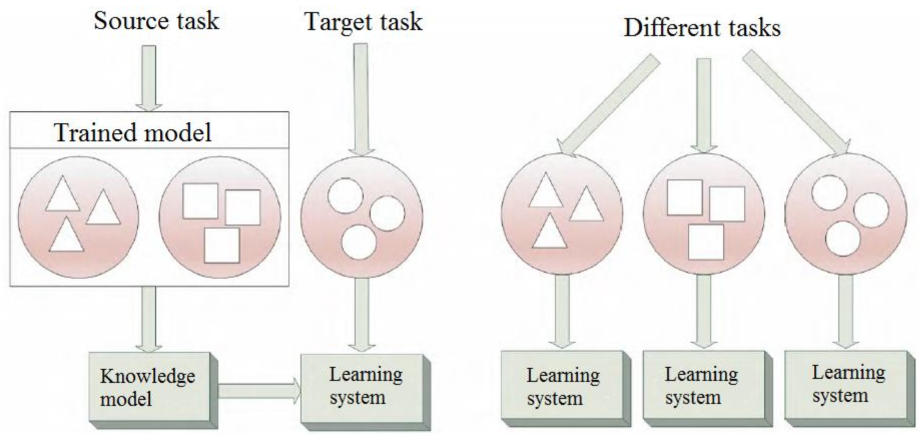

Figure 5. Comparison between traditional machine learning (LEFT) and transfer learning (RIGHT).

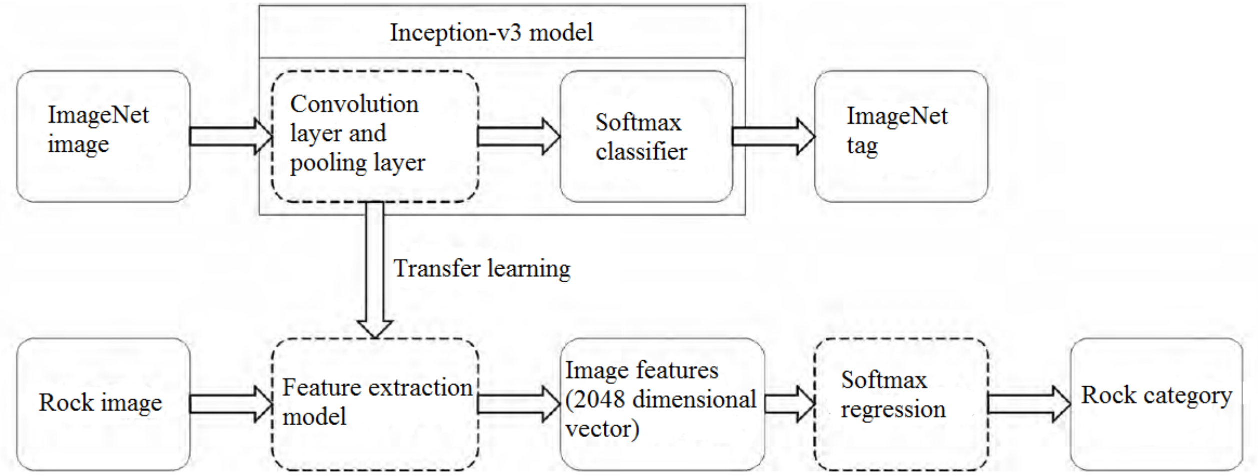

Figure 6. Transfer learning model for automatic identification and classification of minerals.

4. Transfer Learning

Transfer learning is to transfer the learned and trained model parameters to the new model to help the new model training (Yosinski *et al.*, 2014). Considering that most of the data or tasks are relevant, the learned model parameters (also known as the knowledge learned by the model) can be shared with the new model in some way through migration learning, so as to speed up and optimize the learning efficiency of the model without learning from scratch like most networks. There are substantial differences between traditional machine learning and transfer learning, as shown in **Figure 5**.

Migration learning is used to study the automatic recognition and classification of minerals and rocks, which can provide a new means for the automatic classification of rock lithology. Zhang Ye *et al.* (2018) selected three rock images of granite, phyllite and breccia for test, recognition and analysis. The rock image samples used in the experiment are collected by different means such as photos, rock database and network search. The rock types are mainly composed of laboratory rock samples, on-site rock samples and on-site large-scale rock images. In order to make the whole process more intelligent, the scaling and clipping of rock image are automatically completed in the training. The input image only ensures a fixed format, and there are no specific requirements for image size, size and pixel. The author established a rock image depth learning migration model based on Inception-v3. As shown in **Figure 6**, the automatic recognition rate of granite, phyllite and breccia can reach higher than 80%, and some results can even reach higher than 95%. The training process has low requirements for the size, imaging distance and light intensity of rock image, which fully demonstrates its robustness and generalization ability.

5. Algorithm Implementation

With the development of NumPy, SciPy, Matplotlib, Pandas and other program libraries, Python plays an increasingly important role in the field of science (Zhou *et al.*, 2018a).

Scikit-Learn is a library related to machine learning and a powerful machine learning toolkit of Python. It provides a complete machine learning toolbox, including data preprocessing, classification, regression, clustering, prediction, model analysis, etc.

Artificial neural network is a model with powerful function but simple principle. It plays an important role in image recognition, language processing and other fields. Theano is also a python library. It was developed by a deep learning expert Yoshua Bengio. It is used to define, optimize and efficiently solve the simulation estimation problem of mathematical expression corresponding to multi-dimensional array data. It has the characteristics of efficient symbol decomposition, highly optimized speed and stability. The most important thing is that it also realizes GPU acceleration, so that the processing speed of intensive data is dozens of times that of CPU. Theano can build an efficient neural network model, but the threshold is relatively high for ordinary readers.

Therefore, Keras library can be used to build neural network. The application of Keras library can greatly simplify the steps of building various neural network models, and allow ordinary users to easily build and solve the deep neural network with hundreds of input nodes. Keras is not a simple neural network library, but a powerful deep learning library based on Theano. It can be used to build not only ordinary neural networks, but also various deep learning models, such as self encoder, cyclic neural networks, recursive neural networks, convolutional neural networks, etc. As it is based on Theano, it is also quite fast.

The process of building neural network model with Keras is quite simple and intuitive. It is just like building blocks. A very powerful neural network model, even a deep learning model, can be built through just a few dozen lines of code. In the author's teaching and scientific research, it is recommended to build a Python development platform, and the application of Python language can well realize the machine learning algorithm.

6. Conclusion

Through the above discussion, the following understanding can be formed.

(1). Geological big data is growing exponentially. Only by developing intelligent data processing methods can we catch up with the extraordinary growth of big data. Therefore, the development of artificial intelligence geology should be an important development direction.

(2). Machine learning is the fundamental way to make computers intelligent. It is essentially a model training process derived from data, and finally gives a decision oriented to a certain performance measurement.

(3). The purpose of deep learning is to establish and simulate the neural network of human brain for analytical learning, and simulate the mechanism of human brain to interpret data. Its essence is to learn more useful features by building machine learning models with many hidden layers and massive training data, so as to finally improve the accuracy of classification or prediction.

(4). The development of NumPy, SciPy, Matplotlib, Pandas and many other program libraries makes Python occupy an increasingly important position in the field of science. Scikit-Learn and Keras are important toolkits for building machine learning and artificial neural networks using Python.

(5). Although the artificial intelligence geology relying on big data is far from mature, the breakthrough and development of machine learning algorithms make it possible to quickly process massive geological big data and mine valuable and rich information behind them, which will change geology accordingly.

Conflict of interest

The authors declare that they have no conflict of interest.

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Original Research Article

Principle of Machine Learning and Its Potential Application in Climate Prediction

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ABSTRACT

After two "cold winters of artificial intelligence", machine learning has once again entered the public's vision in recent ten years, and has a momentum of rapid development. It has achieved great success in practical applications such as image recognition and speech recognition system. It is one of the main tasks and objectives of machine learning to summarize key information and main features from known data sets, so as to accurately identify and predict new data. From this perspective, the idea of integrating machine learning into climate prediction is feasible. Firstly, taking the adjustment of linear fitting parameters (i.e. slope and intercept) as an example, this paper introduces the process of machine learning optimizing parameters through gradient descent algorithm and finally obtaining linear fitting function. Secondly, this paper introduces the construction idea of neural network and how to apply neural network to fit nonlinear function. Finally, the framework principle of convolutional neural network for deep learning is described, and the convolutional neural network is applied to the return test of monthly temperature in winter in East Asia, and compared with the return results of climate dynamic model. This paper will help to understand the basic principle of machine learning and provide some reference ideas for the application of machine learning to climate prediction.

Keywords: *Machine Learning; Neural Network; Convolutional Neural Network; Climate Prediction; Winter Temperature in East Asia*

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1. Introduction

In 1956, McCarthy *et al.* (1956) put forward the concept of artificial intelligence. Three years later, Samuel (1959) proposed a way to realize artificial intelligence—machine learning. Subsequently, AI experienced two take-off times: the 1960s to 1970s and the 1980s. Nevertheless, AI has not made satisfactory achievements. It has experienced two "AI winter" in the late 1970s and early 1990s. Despite the ups and downs in the development of artificial intelligence, as a branch of artificial intelligence and a way to realize artificial intelligence, the development of machine learning (especially the updating of algorithms) has never stopped, and has gradually developed into an interdisciplinary subject involving probability theory, statistics, approximation theory and so on. In recent years, with the significant improvement of the performance of computer hardware facilities, the massive growth of research data, the significant reduction of storage cost and the obvious improvement of algorithms, machine learning, especially deep learning, has once again back to public's focus and achieved a series of successes. Some machine models trained with a large amount of data can accurately predict new data, such as automatic driving, image recognition and speech recognition, which are successful applications of machine learning (Huntingford *et al.*, 2019).

Human beings have always been committed to understanding and predicting the changes of the world, and the most successful example is numerical weather forecasting. Now, its prediction skills for 3–5 days of 500 hPa geopotential height field in the northern hemisphere have reached more than 90% (Bauer *et al.*, 2015). However, climate prediction on seasonal scale and climate prediction on longer time scale are still great challenges (Hantson *et al.*, 2016). Driven by the in-depth understanding of the climate system change mechanism, the observation data, reanalysis data and numerical simulation data of the earth system have increased rapidly in the past 40 years. In particular, the fifth phase (CMIP5) and the sixth phase of the international coupled model comparison program (CMIP6) provide tens of billions of bytes of data resources for climate change, climate prediction and climate prediction research (Stockhouse & Lautenschlager, 2017). How to fully extract useful information and acquire new knowledge from "big data" poses a new challenge to traditional analysis methods. Machine learning and artificial intelligence bring new opportunities. Machine learning can discover and extract new in-matically identify extreme weather events without any threshold (Liu *et al.*, 2016). In addition, ma-

With the aggravation of climate change and its negative impacts (Pörtner *et al.*, 2019), it is increasingly important and urgent to improve the ability of climate prediction. However, this is still a severe challenge to the current dynamic climate prediction model. Machine learning, supported by high-performance computers, "big data" and advanced algorithms, has improved new ideas and opportunities for improving the skills of climate prediction. This paper will briefly introduce the basic principles of machine learning centred on gradient de-

terrelated signals from the "big data" of the earth system. For example, the SST information of a key area can improve the climate prediction skills of a certain area on land in the coming months. On this basis, artificial intelligence can provide the society with automatic early warning of extreme weather and climate events (Huntingford *et al.*, 2019).

Nowadays, machine learning is gradually combined with climate prediction and weather prediction, and a large number of innovative research results have emerged in related fields. Ham *et al.* (2019) constructed a machine prediction model for ENSO index by using deep neural network. The results show that the prediction skill of deep learning prediction model for ENSO 7–21 months in advance is higher than that of most current dynamic climate prediction models. The shallow neural network machine model can also better distinguish the central and eastern ENSO events (Toms *et al.*, 2020). In addition, machine learning can also be applied to weather forecasting business (Men *et al.*, 2019). Weyn *et al.* (2019) constructed a machine prediction model of 500 hPa potential height grid field by using convolution neural network (deep learning). Its prediction skill of 3 days in advance is obviously better than that of the dynamic barotropic vorticity model, although its performance is still inferior to the current operational numerical weather prediction system. The convolutional neural network machine model can also predict the frontal system of weather scale (Lagerquist *et al.*, 2019) The deep learning model can also auto-chine learning can be used to reduce the uncertainty of future climate prediction (Kuang *et al.*, 2020).
scent, the construction of neural network and the framework of deep learning. Finally, an example of applying deep learning to winter temperature prediction in East Asia is introduced.

2. Introduction to Artificial Intelligence, Machine Learning and Deep Learning

In the 1950s, John McCarthy and others launched the Dartmouth summer artificial intelligence research program (McCarthy *et al.*, 1956) to explore topics such as automatic computers and neural networks. The concept of "artificial intelligence" was born. "Artificial intelligence" aims to endow computers with the ability of "thinking", which refers to the theory and development to realize that computer systems can perform tasks that usually require human intelligence. Obviously, "artificial intelligence" is a concept or general term covering a wide range. The early "artificial intelligence" was mainly realized through hard coding, that is, based on the existing knowledge system of human beings, the code program was designed manually to complete the tasks that challenge human beings. For example, the computer chess player "Dark Blue" designed by IBM is to fully formalize the rules of chess and then describe them to the computer through hard coding. "Dark blue" defeated world chess champion Gary Kasparov on May 11, 1997. However, with the improvement of practical application requirements and the limitations of human cognitive system, the bottleneck of hard coded "artificial intelligence" began to show: It can not solve more complex problems. In order to make up for the disadvantage that hard coding has high requirements on human cognitive system, scientists put forward a new idea of building "artificial intelligence", that is, to make it the characteristic of computer to automatically generalizing and summarizing information from big data, i.e. machine learning. Although machine learning still needs to be realized through coding, it has a feature that is obviously different from the traditional hard coding method. In the early stage of task execution, the computer does not give specific rules to solve the problem (such as the known chess rules of "dark blue"), but uses a large amount of data and constantly "trains" the computer through some algorithm. At the same time, a loss function is used to measure the learning effect of the computer, and the direction of "training" is adjusted through the optimization algorithm. Through repeated iterative calculation, the computer finally has the optimal scheme or rules to solve the problem (i.e. Parameters, see Section II). In this way, the "trained" machine can be put into practical application, such as face recognition and speech recognition system, which are the results of machine learning. It can be seen that algorithm is the core of machine learning, and neural network is one of the classical algorithms. Deep learning is to realize machine learning by using neural networks with more levels (i.e. the meaning of depth).

3. Principles of Machine Learning

Machine learning can be divided into supervised learning, unsupervised learning and reinforcement learning (Dougherty *et al.*, 1995). This paper mainly focuses on supervised learning. The characteristic of supervised learning is that each "training data" has a clear output expectation (i.e. "label data"). In order to explain the "learning" process of the machine simply and clearly, we take the simplest linear regression as an example to show how to continuously "train" the machine and finally obtain the parameters of the linear regression equation (i.e. slope θ_1 and intercept θ_2). Build a linear function: $y = 2.5x + 3.5 + \delta$ ($x = 1, 2, 3, \ldots, 20$), among which δ represents the noise data conforming to the random normal distribution. The mapping relationship between x and y is shown in the scatter diagram of **Figure 1**(A). From the perspective of machine learning, x is called "training data" and y "label data" (**Table 1**).

Input the "training data" x into the computer and randomly give any two initial parameters of the computer, namely slope θ_1 and intercept θ_2. Since the goal of the computer is to "learn" a linear relationship, the "predicted value" $\hat{y}$ of the corresponding output should meet $y = \theta_1^0 \times x + \theta_2^0$. In order to evaluate the "learning" effect of computer, that is, to measure the difference between $\hat{y}$ and y, a cost function, also known as loss function, needs to be introduced. Root mean square error is selected here:

$$\sum_{i=1}^{m}(\hat{y}_i - y_i)^2 \tag{1}$$

Table 1. "Training data" denotes x, the "label data" denotes y, and "random noise data" denotes δ

X	Δ	Y
1	0. 57	6. 57
2	-0. 39	8. 11
3	0. 19	11. 19
4	-0. 78	12. 72
5	2. 5	18. 5
6	1. 48	19. 98
7	0. 27	21. 27
8	-0. 82	22. 68
9	-1. 58	24. 42
10	-0. 86	27. 64
11	-0. 31	30. 69
12	-0. 91	32. 59
13	-1. 64	34. 36
14	0. 47	38. 97
15	0. 63	41. 63
16	0. 17	43. 67
17	-0. 78	45. 22
18	-0. 57	47. 93
19	-0. 25	50. 75

Of which M represents the number of data sets. Since "training data" x and "label data" y are determined data sets, and only parameters θ_1 and intercept θ_2 are uncertain, so the loss function written as $f(\theta_1, \theta_2)$ is actually about θ_1 and θ_2. For the convenience of description, the parameters are expressed in the form of vectors $\Theta(\theta_1, \theta_2)$. In other words, the ultimate goal of "training" the machine is to adjust the parameters Θ and make the value of $f(\Theta)$ reaches the minimum.

According to the principle of derivative function, that is, $f(\Theta)$' derivative function $\nabla f(\Theta)_{|(\theta_1^0, \theta_2^0)}$ at certain point $\Theta^0(\theta_1^0, \theta_2^0)$ represents the fastest direction that $f(\Theta)$ increases. In order to effectively "learn" towards the minimum value of $f(\Theta)$, the machine can adjust parameters along the opposite direction of the derivative function to obtain new parameters $\Theta^1(\theta_1^1, \theta_2^1)$, namely:

$$\Theta^1 = \Theta^0 - \alpha \times \nabla f(\Theta)_{|\Theta^0} \tag{2}$$

If Θ^1 is not the parameter when $f(\Theta)$ reaches its minimum value, then the machine continue to adjust the parameter along the opposite direction of the derivative function to obtain new parameters θ_2, namely:

$$\Theta^2 = \Theta^1 - \alpha \times \nabla f(\Theta)_{|\Theta^1} \tag{3}$$

Among them, $\alpha \in (0,1)$ is called "learning efficiency". By iterating the above calculation process repeatedly, the computer will continuously reduce the loss function $f(\Theta)$, and lock the parameter until it is less than a critical value Θ. At this time, the parameter $\Theta(\theta_1^n, \theta_2^n)$ (n represents the final number of iterations) "learned" by the computer will make the "predicted value" $\hat{y}$ approach the "label data" y optimally. The above process of adjusting parameters along the opposite direction of derivative function is called "gradient descent" method (Ruder, 2016); The module similar to adjusting parameters is called "optimizer".

Return to the problem of machine learning to solve the above linear regression. In order to make the description easier, the above "predicted value" $\hat{y}$ "training data" x, parameters (θ_1, θ_2) and "label data" y are expressed in the form of matrix respectively:

$$\hat{Y} = \begin{pmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_{20} \end{pmatrix},$$

$$X = \begin{pmatrix} x_1 & 1 \\ x_2 & 1 \\ \vdots & \vdots \\ x_{20} & 1 \end{pmatrix},$$

$$\Theta = \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix},$$

$$Y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_{20} \end{pmatrix}.$$

Therefore, the loss function can be expressed as:

$$f(\Theta) = \frac{1}{2m}(X \cdot \Theta - Y)^{\mathrm{T}}(X \cdot \Theta - Y) \tag{4}$$

Of which: m is the number of each data set, i.e. 20, and the constant 1/2 is to avoid redundant constants in the subsequent derivation function. The derivative function of the loss function is:

$$\nabla f(\Theta) = \frac{1}{m} X^{\mathrm{T}}(X \cdot \Theta - Y) \tag{5}$$

Firstly, the initial parameter of the computer given randomly $\Theta^0(20, -20)$ is substituted into formula (4) and formula (5) together with "training data" x and "label data" y (**Table 1**), and the loss function and its derivative can be obtained:

$f(20. -20) = 17\,934.65,$

$$\nabla f(\Theta)_{|\Theta^0(20,-20)} = (\frac{\partial f}{\partial \theta_1}, \frac{\partial f}{\partial \theta_2})_{|\Theta^0(20,-20)} = (2264.65, 160.25)$$

At the same time, the "learning" efficiency of the machine α is set to 0.01. According to formula (2), the machine updates the parameters to:

$$(\theta1, \theta2) = (20, -20) - 0.01 \times (2264.65, 160.25) = (-2.646, -21.603)$$

The machine continuously updates the parameter (θ_1, θ_2) through the above "learning" process (**Figure 1**B), and the value of the loss function continues to decrease (as shown by the red line in **Figure 1**(C). After about 3000 iterative calculations, the parameter (θ_1, θ_2) basically tends to be stable (**Figure 1**B), indicating that the loss function has approached its minimum value, and this point (θ_1^n, θ_2^n) is also the position where the derivative of the loss function is the smallest (i.e. The slope is the smallest). Set the critical value $\nabla f(\theta_1^n, \theta_2^n)$ of the derivative function to 10 × 10^{-5}, that is, when the value of the derivative function is less than the critical value, the machine will stop "learning" and lock the parameter (θ_1^n, θ_2^n) at this time, i.e. (2.50,3.53). Therefore, the linear fitting curve finally "learned" by the machine is: $\hat{y} = 2.50x + 3.53$ (**Figure 1**A: red line), which basically conforms to the linear relationship between "training data" x and "label data" *y* (**Figure 1**A: scattered points).

Of course, the above is only the process of "training" the machine. The ultimate goal of machine learning is to use the "trained" machine (i.e. complete the optimization of parameters) to predict the new data (commonly referred to as "test data") that the machine has never engaged before. It will be described in detail in section III and section IV.

4. The Idea of Applying Neural Network to Climate Prediction

Linear regression is a common method in climate prediction and climate change research. Of course, the linear regression function can be calculated quickly without machine learning. However, in the process of practical research and application, we often face a large number of observation and numerical simulation data. Due to the complexity of the climate system, there may be some nonlinear relationship between the data, and the above machine learning model based on linear relationship will lose its function. At this time, deep learning can give play to its great advantages. Deep learning is based on neural network, which usually includes one input layer, several hidden layers and one output layer. Each neural layer contains several neurons (in fact, it represents the node containing a specific data). The input layer is responsible for receiving "training data" or "test data", and the output layer is responsible for exporting "prediction data". The main function of the hidden layer is to connect the input layer and the output layer through a large number of parameters. The loss function can be constructed by using the "prediction data" of the output layer and the known "label data", and then the loss function can be reduced and the parameters can be adjusted through the optimizer. When the loss function reaches the minimum value, the parameters will be locked, that is, complete the "training" of the machine (see Section 2). The key question here is: how do neurons connect between input layer, hidden layer and output layer? The answer is: matrix multiplication.

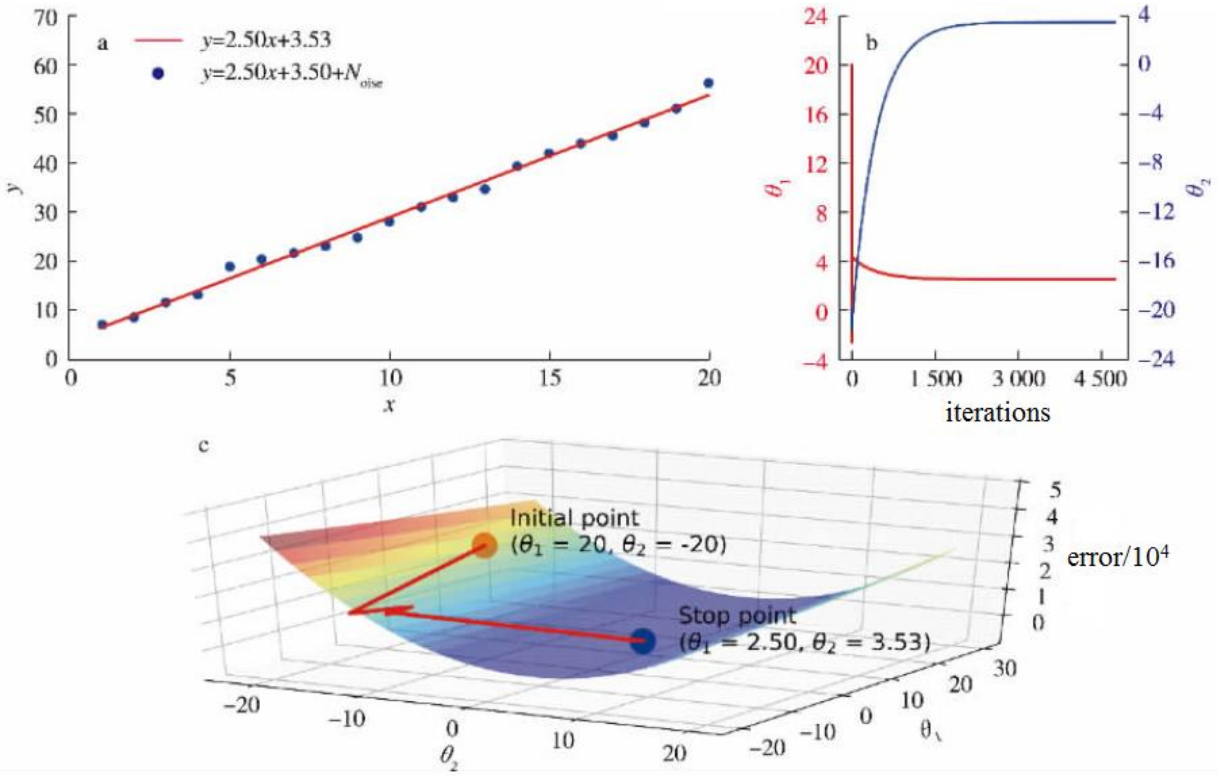

Figure 1. (A) Scatters indicate the mapping relationship between the 'train data' x and 'labeled data' y, the red line indices the linear fitting by machine linear; (B) the updating of weights along the iteration; (C) the gradient descent of machine learning.

For simplicity, first build a shallow neural network: an input layer containing a neuron node; two hidden layers, including 4 and 5 neuron nodes respectively; an output layer contains a neuron node (**Figure 2**A). We will gradually analyze the connection mode between neurons from the perspective of matrix multiplication.

1). Input layer to first hidden layer

Because the input layer has only one neuron, i.e. only one data, it can be regarded as a matrix $\boldsymbol{X} = [x_1^1]$ with one row and one column. The subscript of x_i^j here represents the j-th characteristic data of the i-th sample. $x_1^1$and x_1^2 for example, can represent the temperature and precipitation of an observation station at the first observation time, and so on (the same below). The hidden layer contains 4 neurons, i.e. 4 data, which can be expressed as a matrix with one row and four columns $\boldsymbol{Y} = [y_1^1, y_1^2, y_1^3, y_1^4]$. In order to realize the mapping between matrices $\boldsymbol{X}$ and $\boldsymbol{Y}$, a parameter matrix with one row and four columns $\boldsymbol{\omega} = [\omega_{11}, \omega_{12}, \omega_{13}, \omega_{14}]$ can be constructed. Therefore, the $\boldsymbol{X} \cdot \boldsymbol{\omega} = \boldsymbol{Y}$ connection between the input layer and the neurons of the first hidden layer is realized (**Figure 2**B).

2). First hidden layer to second hidden layer

There are five neurons in the second hidden layer, which can be expressed as a matrix with one row and five columns $\boldsymbol{Z} = [z_1^1, z_1^2, z_1^3, z_1^4, z_1^5]$. According to the above ideas, a new parameter matrix with five rows and five columns **θ** needs to be constructed. So $\boldsymbol{Y} \cdot \boldsymbol{\theta} = \boldsymbol{Z}$ realizes the connection between the neurons of the first hidden layer and the second hidden layer (**Figure 2**B).

3). Second hidden layer to output layer

There is only one predicted value P_1 in output layer, so it is only necessary to build a new parameter matrix with five rows and one column **μ** and the connection between hidden layer 2 and output layer neurons can be realized (**Figure 2**B).

After the above neural network is constructed, a batch of "training data" sets (assuming n samples) can be input into the neural network to obtain n numbers of "prediction data" sets. Combined with the corresponding n number of "tag data", we can get the information about $\boldsymbol{\omega}$,$\boldsymbol{\theta}$ and $\boldsymbol{\mu}$ of the loss function $f(\boldsymbol{\omega}, \boldsymbol{\theta}, \boldsymbol{\mu})$. Then, the optimizer continuously reduces the loss function and updates the parameters $\boldsymbol{\omega}$,$\boldsymbol{\theta}$ and $\boldsymbol{\mu}$ at the same time (**Figure 2**B); see Section IV). It is worth noting that in order to explore the nonlinear relationship between the hidden layer and its front and rear layers, the neural network will introduce a nonlinear "excitation function" into the hidden layer. This is also the reason why the neural network algorithm is superior to the linear model (Specht, 1991).

In order to intuitively show the learning effect of neural network, a nonlinear function $y' = \sin(3.5 \times \cos(2.5\theta))$ is constructed. θ is 300 equally spaced data between –1 and 1, i.e. the "training data" set; the function curve between y' and θ is shown in the blue line of **Figure 3**(A). A certain random noise is superimposed on the nonlinear function to obtain 300 "tag data" y. The mapping result between θ and y is shown in **Figure 3**(A). Building a neural network includes one input layer, two hidden layers (including 16 neurons respectively) and one output layer. Input the "training data" θ into the neural network and use the hyperbolic tangent function (TANH) excitation function in the hidden layer (**Figure 3**B). When the machine goes through 6000 iterations, the output value learned by the machine is shown in the yellow line in **Figure 3**(A). At this time, the value of the loss function is 0.01. It can be seen that neural network machine learning has a good performance in solving nonlinear problems. When the rectified linear unit (RELU) "excitation function" (**Figure 3**C) is adopted, the output value of the machine after 6000 iterations is as the red line in **Figure 3**(A), and the value of the loss function is 0.052.

The neural network constructed above aims at the input layer with only one eigenvalue $[x_1^1]$ (**Figure 2**A). If the input layer needs to process multiple eigenvalues, such as the East Asian winter temperature index predicted with the autumn Arctic sea ice index and the autumn Eurasian snow index (i.e. the two eigenvalues of the input layer correspond to one output value), how to build a neural network? At this time, it is only necessary to increase the number of neurons in the input layer to two (i.e. the input layer matrix is two columns $[x_1^1, x_1^2]$) and the parameter matrix multiplied by it to two rows (**Figure 2**B), so as to complete the construction of neural network with two eigenvalues in the input layer, and the process goes on. Due to the complexity and diversity of climate systems and the nonlinear interaction between climate systems (Hasselmann, 1999), machine learning will be used to build climate prediction models in the future to further improve the skills of climate prediction.

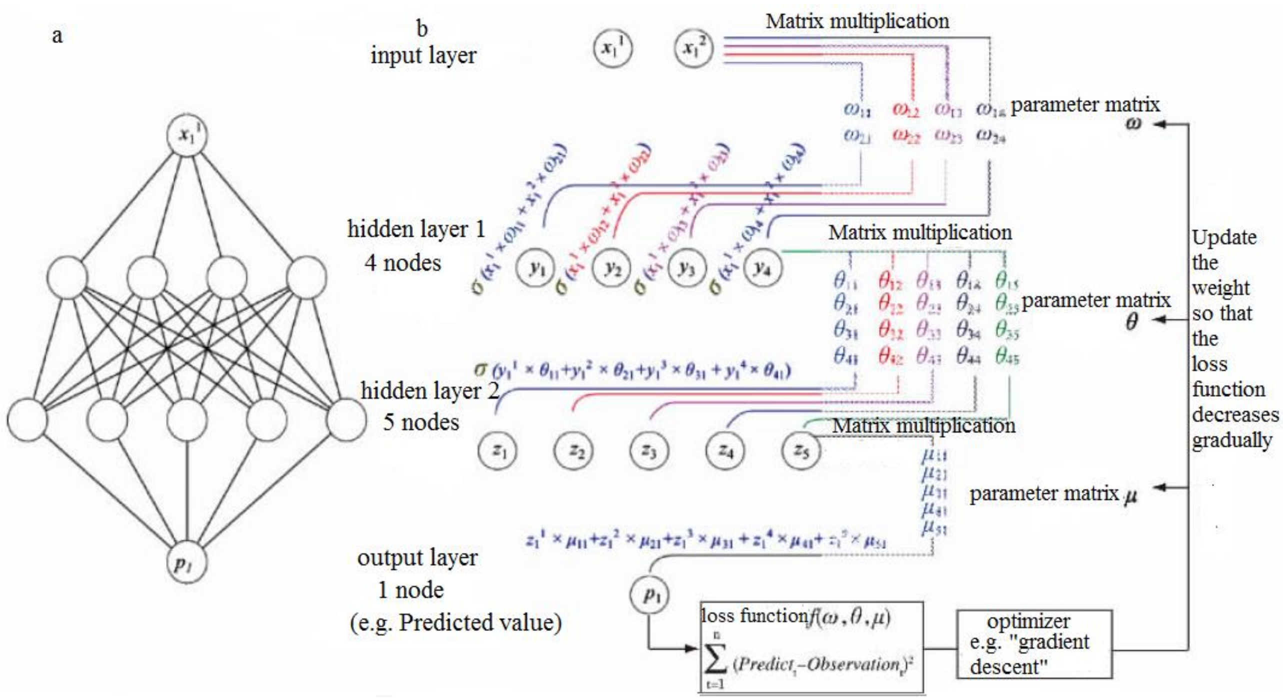

Figure 2. (A) A shallow neural network; (B) illustrating the architecture of neural network.

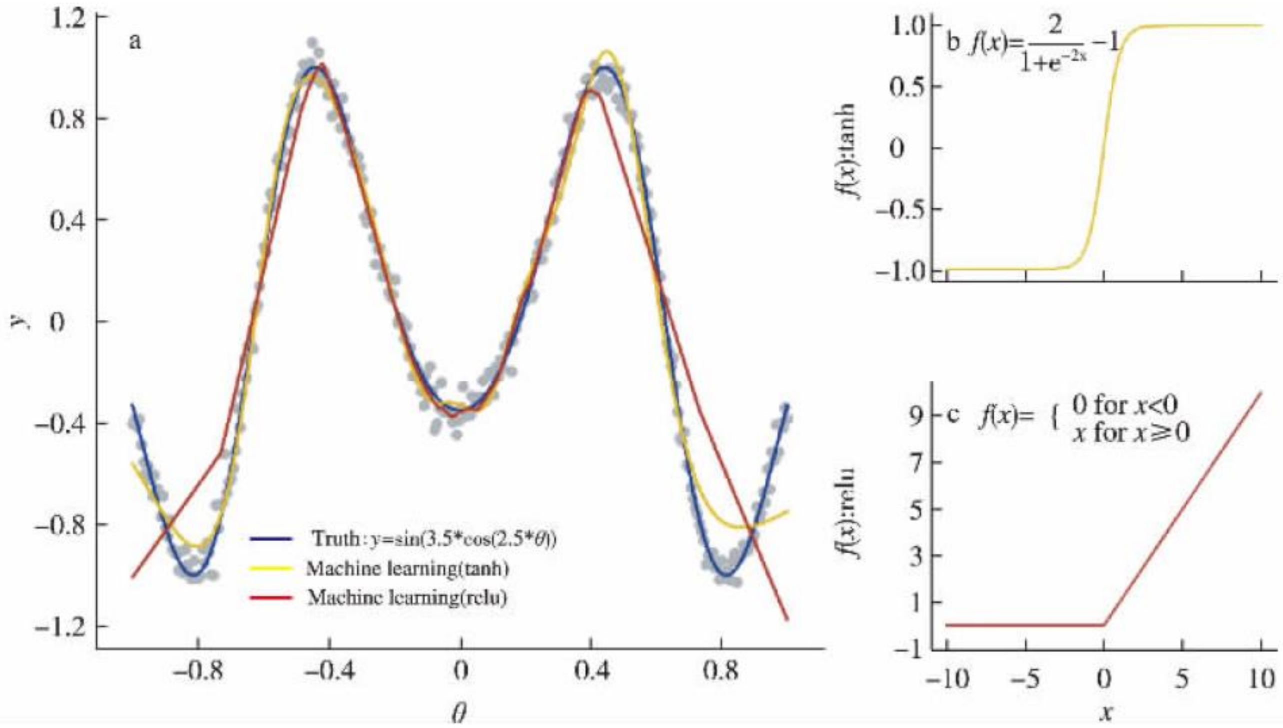

Figure 3. (A) Non-linear fitting by neural network with different activation functions; the blue curve indicates the 'true' curve of non-linear function; scatters indicate the non-linear function $f(\theta) = \sin(3.5 \cos(2.5\,\theta))$ overlapped by random noise; the yellow and red curves are results of machine learning with activation function of tanh and relu, respectively; (B) and (C) illustrate the activation function of tanh and relu, respectively.

5. Deep Learning: Convolutional Neural Network and Its Application to Winter Temperature in East Asia

Convolutional neural network (CNN) adds one or more convolutional layers and pooling layers on the basis of ordinary neural network, including maximum pooling and average pooling (Goodfellow *et al.*, 2016). The process of convolution is as follows. Firstly, a convolutional kernel, i.e. a weight matrix, is randomly given, whose dimension is the same as that of the convoluted data, but the horizontal resolution is smaller. The convolution kernel extracts data subsets from the convoluted data in a fixed step according to its own resolution, multiplies them correspondingly, and then sums them, until the retrieval of all data is completed. In order to consider the nonlinearity of the data, the convoluted data will go through an "excitation function", and the final output result will enter the pooling layer (see "step 1" in **Figure 4**).

Pooling (taking the maximum pooling as an example) is based on the specified horizontal resolution (such as 2 × 2) retrieve the output data of the convolution layer according to the specified step size, and output the maximum value within the range of the grid point every time until the retrieval of all data is completed (see "step 2" in **Figure 4**). Two points need to be pointed out.

1). Only one convolution kernel is used in **Figure 4**, so the data after convolution is still two-dimensional. In fact, multiple different convolution check data can be used for convolution, and each convolution kernel convolutes the data according to the above process. Therefore, when all convolution cores complete the convolution process, the horizontal resolution of the output data will be significantly reduced and one dimension will be added (equal to the number of convolution cores).

2). In **Figure 4**, there is only one convolution layer and one pool layer. In practical application, the above convolution and pooling process can be repeated for many times, i.e. the pooled data will undergo convolution and pooling. Convolution kernel, convolution layer and the number of pool layers need to be adjusted according to specific problems and test results. Convert the pooled data into one-dimensional data and input it into the input layer of ordinary neural network, then the construction of convolutional neural network can be completed (see "step 3" in **Figure 4**). Convolutional neural network has achieved great success in computer vision (such as image classification and recognition) and natural language processing (Goodfellow *et al.*, 2016; Huntingford *et al.*, 2019). Two dimensional or three-dimensional data are often used in climate prediction research and application. Therefore, in theory, convolutional neural network can be applied to the field of climate prediction. In addition, the abundance of climate system observation data and numerical simulation data provides sufficient training data for machine learning. In order to try to apply convolutional neural network to climate prediction, this paper uses convolutional neural network method and uses the historical simulation data of the fifth stage coupled model comparison program (CMIP5) to construct a machine prediction model for the monthly temperature index in winter in East Asia. Then input the trained machine prediction model with the historical observation data to carry out the return test on the historical observation time series of monthly temperature in winter in East Asia. The research data, modeling methods and return results are as follows.

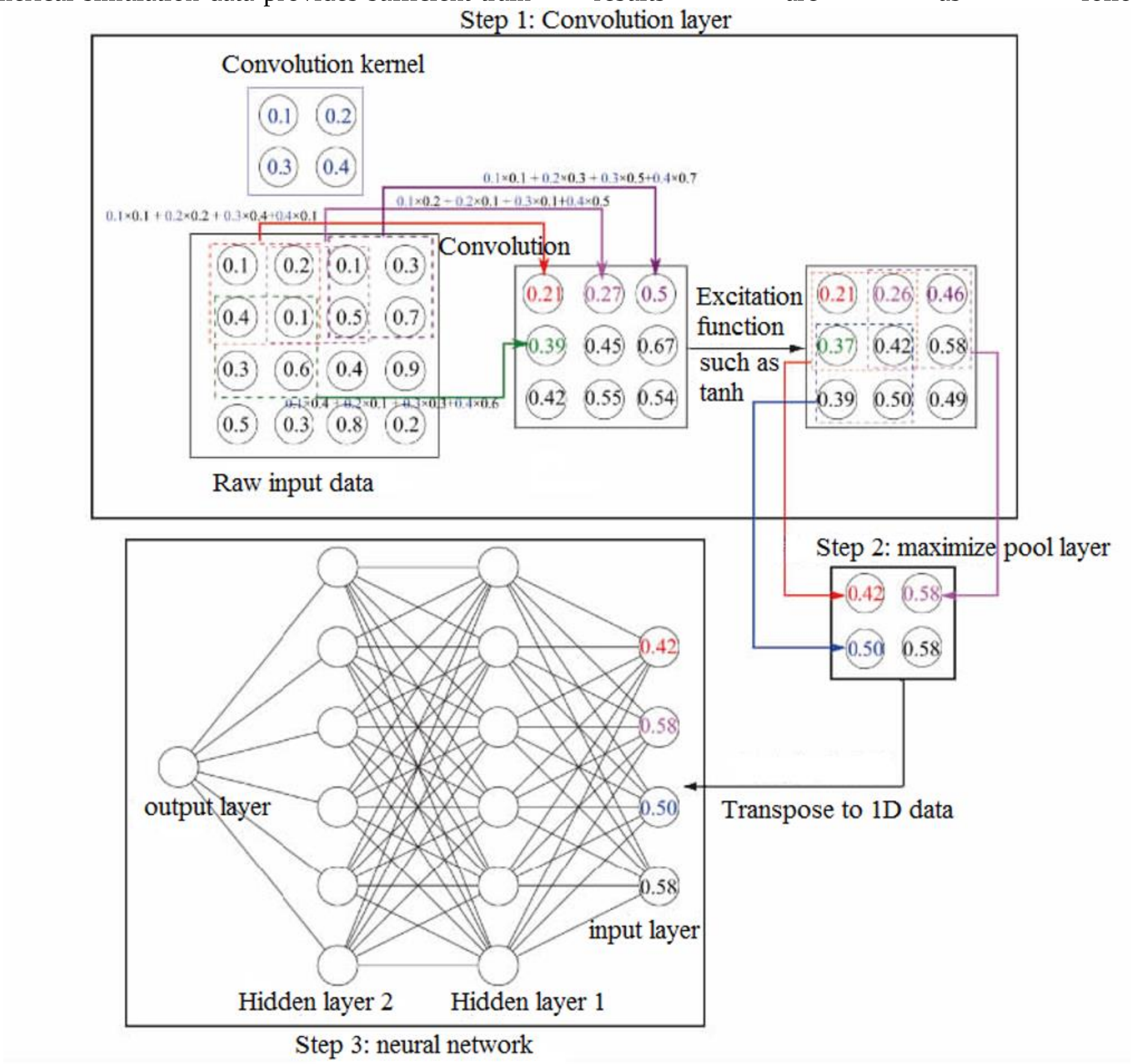

Figure 4. The architecture of revolutionary neural network.

5.1 Research data

The historical simulation data of 21 climate models are taken from CMIP5 from 1861 to 2005, and variables include surface temperature T2m, sea surface temperature SST and 0–300m average ocean temperature T300 (https://esgf-node.llnl.gov/projects/cmip5/). The historical return test results of dynamic climate model CanCM 4i are taken from https://iridl.ldeo.columbia.edu/SOURCES/.Models/NMME/. Observation data include the following. 1). SST data from the global ocean data assimilation system (GODAS) of the National Center for Environmental Prediction (NCEP) (https://psl.noaa.gov/data/gridded/data.godas.html; Behringer & Xue, 2004) from 1982 to 2018. 2). The surface temperature T2m in the reanalysis data (ERA5) of the European Center for medium and long term forecasting is from 1982 to 2018 (C3S, 2017). In order to save the training time of the machine, the SST and T300 of CMIP5 and GODAS are interpolated to 5° × 5° horizontal resolution, ranging from 60° s to 60° n, 0°–360°, i.e. the grid resolution is 24 (Zonal) × 72 (meridional direction).

5.2 Modeling method

1). Build machine “training data” Train_data, “label data” Labeled_data and “test data” Test_data (**Table 2**).

Firstly, T2m, SST and T300 in all data are transformed into anomaly fields (minus the climate state in the corresponding data period), and the anomaly fields in CMIP5, GODAS and EAR5 are recorded as CMIP_SSTA, CMIP_T300A, CMIP_T2mA, GODAS _SSTA, GODAS_T300A, ERA5_T2Ma respectively. It is planned to forecast East Asia winter month by month (i.e. December, January and February) with one month in advance. The prediction factors are SST and T300 anomaly field for three consecutive months in the early stage.

Table 2. Machine learning model and its training data (Train_data), labeled data (Labeled_data), testing data (Test_data) and prediction (Prediction)

Machine model	Training data	Lable data	Test data	Estimate
ML1	CMIP_SSTA and CMIP_T300A of September, October and November 1861–2004, recorded as Train_data1	The regional average value of CMIP_T2mA of a region in East Asia (100° ~ 140°E, 10° ~ 30°N) in December 1861–2004 is recorded as CMIP_T2m_Dec	GODAS_SSTA and GODAS_T300A of September, October and November 1982–2017, recorded as Test_data1	The regional average value T2mA in a region of East Asia (100° ~ 140°E, 10° ~ 30°N) in December 1982–2017 is recorded as Pre_T2m_Dec
ML2	CMIP_SSTA and CMIP_T300A of October, November and December 1861–2004, recorded as Train_data2	The regional average value of CMIP_T2mA of a region in East Asia (100° ~ 140°E, 10° ~ 30°N) in January 1862–2005 is recorded as CMIP_T2m_Jan	GODAS_SSTA and GODAS_T300A of October, November and December 1982–2017, recorded as Test _data2	The regional average value T2mA in a region of East Asia (100° ~ 140°E, 10° ~ 30°N) in January 1983–2018 is recorded as Pre_T2m_Jan
ML3	CMIP_SSTA and CMIP_T300A of November and December 1861–2004 and January 1862–2005, recorded as Train_data3	The regional average value of CMIP_T2mA of a region in East Asia (100° ~ 140°E, 10° ~ 30°N) in February 1862–2005 is recorded as CMIP_T2m_Feb	GODAS_SSTA and GODAS_T300A of November and December 1982–2017 and January 1983–2018, recorded as Test_data3	The regional average value T2mA in a region of East Asia (100° ~ 140°E, 10° ~ 30°N) in February 1983–2018 is recorded as Pre_T2m_Feb

In order to test the prediction effect of the machine prediction model, the regional average value of ERA5_T2mA in East Asia (100° ~ 140°E, 10° ~ 30°N) from 1982 to December 2017, 1983 to January 2018 and 1983 to February 2018 were further calculated, and they are recorded as ERA5_T2m_Dec, ERA5_t2m_Jan and ERA5_T2m_Feb respectively. It is worth noting that in order to obtain enough training data samples as much as possible, the full-time data of CMIP5 historical simulation test is used, resulting in a certain overlap between the training data and the test data. However, considering that the correlation coefficient between the climate interannual variability simulated by CMIP5 coupling model and the observation results is very weak, the above overlap will not have a significant impact on the prediction effect of machine learning.

2). Structure of convolutional neural network prediction model.

The convolutional neural network consists of three convolution layers and two maximum pooling layers. The last convolution layer is fully connected with the ordinary neural network. The ordinary neural network contains a hidden layer. The convolution kernel size of the first convolution layer is 8 × 4, and the convolution kernel size of the second and third convolution layers is the grid resolution of 4 × 2. The maximum pool level retrieves the maximum value from the convolution layer with its grid resolution of 2 × 2. In order to obtain a more objective prediction structure, two different numbers (i.e. 30 and 50) of convolution nuclei and hidden layer neurons are tried. For example, C30H50 represents a Convolution Neural Network with 30 convolution nuclei and 50 hidden layer neurons, and so on. At the same time, each convolutional neural network adopts 10 different initial weights for training, and carries out the corresponding return test.

5.3 Return results

Figure 5 shows the temperature index of December, January and February in winter in East Asia which returned one month in advance by the convolutional neural network machine model, which is recorded as Pre _T2m_Dec, Pre_T2m_Jan, Pre_T2m_Feb respectively. The results show that the correlation coefficients between the set average return result of convolutional neural network Pre _T2m_Dec, Pre_T2m_Jan, Pre_T2m_Feb and observation results in December, January and February ERA5_T2m_Dec, ERA5_T2m_Jan, ERA5_T2m_ Feb are 0.77, 0.82 and 0.70 respectively. At the same time, the amplitude of the return index is also close to the observation. It is worth noting that the prediction results of Convolution Neural Network with different numbers of convolution nuclei and hidden layer neurons are not very different. However, the prediction results of different initial fields (shown in the shadow of **Figure 5**) are significantly different. The deepening of neural network can improve the prediction ability of the machine to a certain extent. For example, the return effect of C50H50 in **figure 6**A and **figure 6**B is slightly better than that of C50H30. However, when the neural network structure reaches a certain depth, it becomes particularly important to find the global optimal parameters of the neural network by controlling the initial field. For example, take different initial parameters for the same machine prediction model to train the machine (**Figure 6**: C50H50), the difference between the return result and the observed correlation coefficient can be up to about 0.2 between different sets.

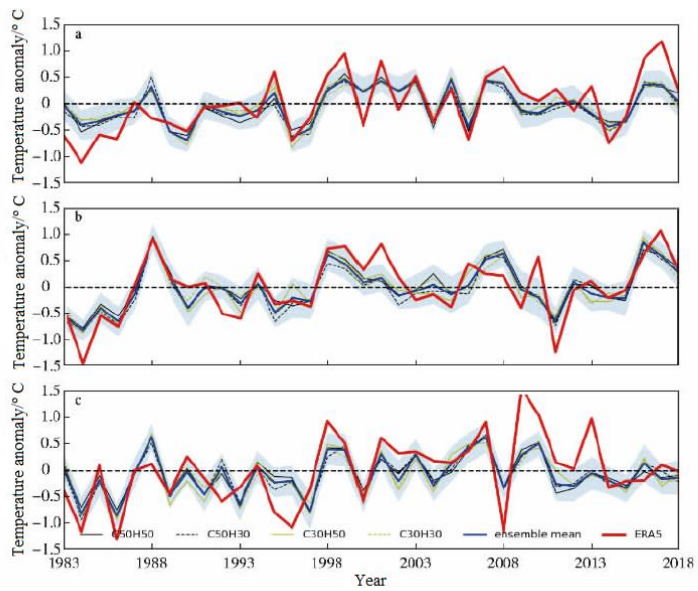

Figure 5. Ensemble-mean time series of (A) December 1982-2017, (B) January 1983-2018, (C) February 1983–2018 aera-averaged (10°-30°N,100°-140°E) T2m anomalies for one-month-lead hindcast using convolutional neural network (CNN) model (blue solid curves) as well as the corresponding observed time series (red curves). Other curves represent results of CNN model with different numbers of convolutional filters and hidden layers; for example, C50H30 indicates the CNN model with 50 convolutional filters and 30 hidden layers, and so on; shading indicates±1 standard deviation of 40 ensemble members.

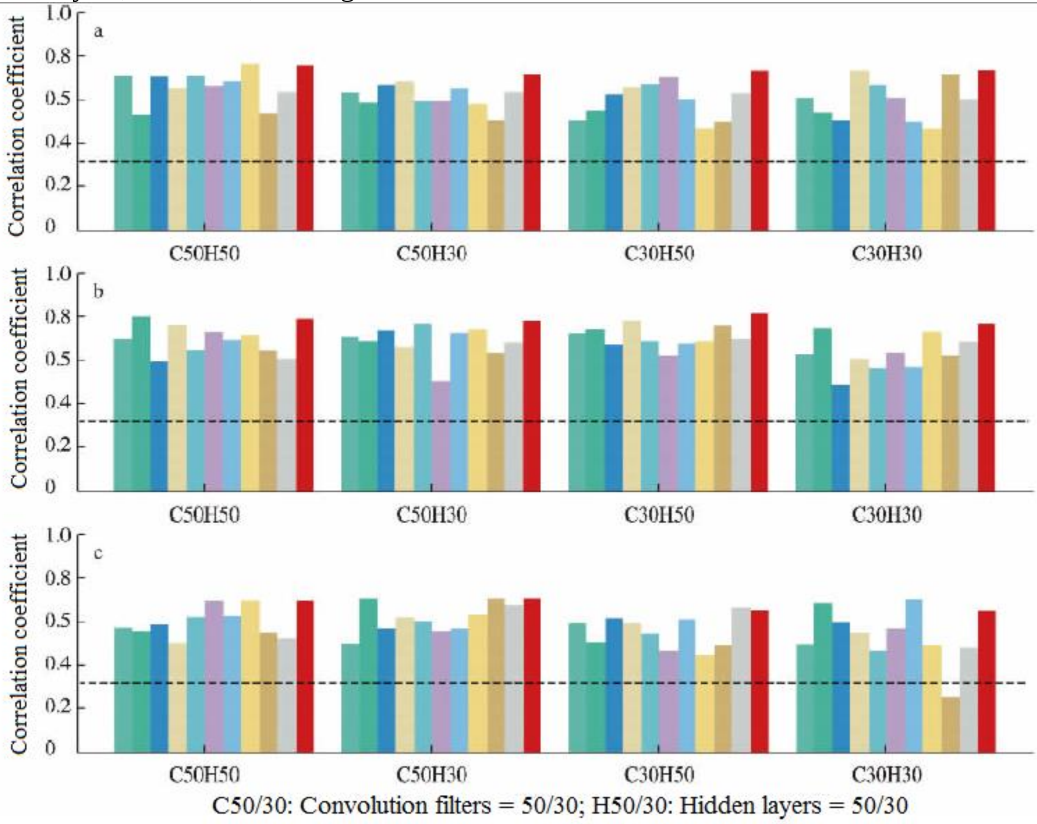

Figure 6. Dataset are the same as Figure 5, but for the correlation coefficients of each ensemble members with the observation in (A) December, (B) January, and (C) February; the red bar indicates the results of ensemble mean in each CNN model; the horizontal dashed line indicates the value at 95% confidence level.

It should be emphasized that the return effect of the in-depth learning model is better than that of the climate dynamic model. As shown in **Figure 7**, the correlation coefficient between the 40 collective return tests and the observation results of the January temperature in a region of East Asia (100° ~ 140°E, 10° ~ 30°N) returned one month in advance by the deep learning model is 0.5–0.8. All passed the 95% reliability test. At the same time, it is also higher than the correlation coefficient (0.42) between the dynamic model CanCM 4i return results and observations. In addition, the temperature skill of a region in East Asia (100° ~ 140°E, 10° ~ 30°N) returned by the deep learning model 2–3 months in advance is generally higher than the return effect of the dynamic model.

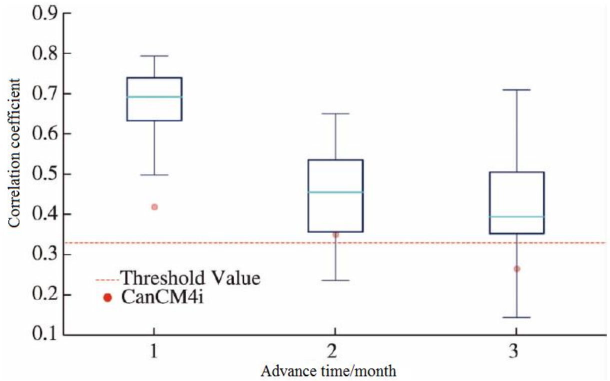

Figure 7. Boxplot for correlation coefficients of observation with each ensemble member's hindcast with one month,two months, and three months in advance; red dot indicate the correlation between the observation and the hindcast by cancm4i; the horizontal dashed line indicates the value at 95% confidence level.

It is worth noting that although the above examples show that machine learning can be applied to short-term climate prediction, however, it does not mean that give any “big data” to the machine, a climate prediction model with good performance can be established. In order to establish a machine learning climate prediction model with high prediction skills, it is necessary to fully understand the climate dynamics behind “big data”. In other words, the establishment of machine learning model guided by climate dynamics is very important to give full play to the potential of machine learning in climate prediction. For example, using the same machine learning idea as **Figure 5**B, the return model is established for the average temperature in January at low latitude (100° ~ 140°E, 0° ~ 20°N) and middle latitude (100° ~ 140°E, 30° ~ 50°N). The correlation coefficient between the return result of collective average and the observation result is 0.89 and 0.33 respectively (**Figure 8**). The main reason may be that compared with the climate in middle and high latitudes, the climate in low latitudes is more obviously affected by tropical and subtropical SST (**Figure 9**). The prediction factors in the machine learning prediction model in this paper are mainly the sea surface temperature anomaly of 60°S ~ 60° N and the ocean heat content anomaly of 0 ~ 300m. From the perspective of climate dynamics, the machine learning prediction model in this paper is more suitable for climate prediction in middle and low latitudes. If the machine learning prediction model of mid and high latitude climate is to be established, the impact of mid and high latitude climate system needs to be considered more, such as Eurasian snow, Arctic sea ice, polar vortex, etc. (He *et al.*, 2016; He *et al.*, 2020). It should be emphasized that although the linear regression analysis shows that there is a significant statistical relationship between the temperature anomaly in the low latitude of East Asia and the sea surface temperature in some parts of the world, the return result of the linear regression model based on sea surface temperature is far less than that of machine learning (**Figure omitted**). It further shows the obvious advantages of machine learning in exploring nonlinear processes.

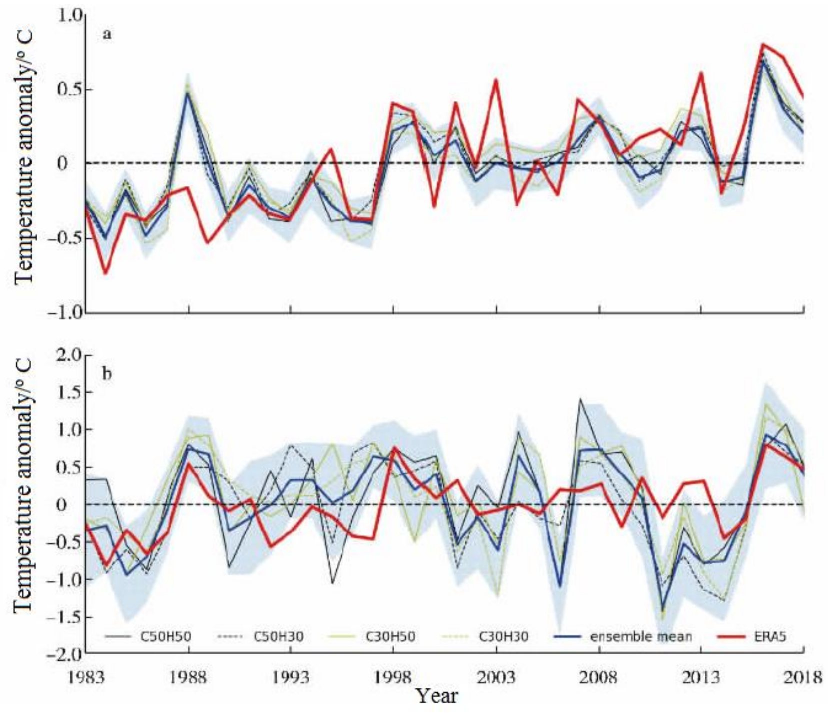

Figure 8. Same as **Figure 5** (B), but for the hindcast of area-averaged T2m anomalies in January 1983—2018 over (A) 0°—20°N,100°—140°E and (B) 30°—50°N,100°—140°E.

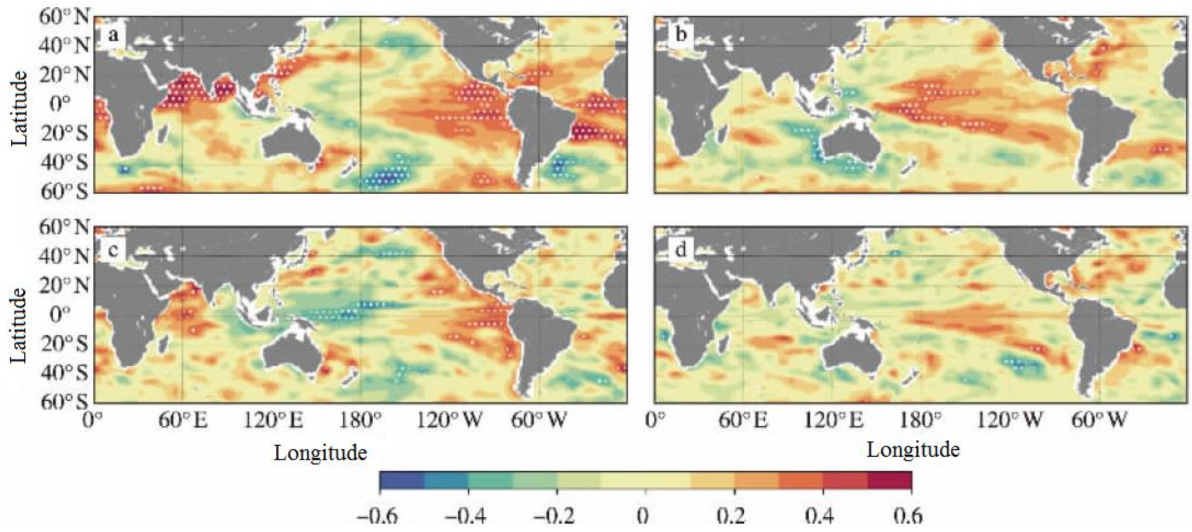

Figure 9. Correlation coefficients (SHADING) of area-averaged T2m anomalies over (0°—20°N,100°—140°E) in January 1983—2018 with the preceding three months'mean (October,November,December) (A) sea surface temperature anomalies and (B) oceanic heat content anomalies from surface to 300m; regions with stippling indicate the values significant at 95% confidence level; (C) and (D) are the same as (A) and (B),respectively,but for the area-averaged T2m anomalies over (30°—50°N,100°—140°E) in January 1983–2018.

6. Summary and Discussion

With the vigorous development of machine learning, this paper focuses on the basic principle of supervised learning of machine learning and analyzes the potential application of machine learning in climate prediction through machine learning examples of linear, nonlinear and deep learning.

Firstly, by introducing a simple example of machine learning to obtain the parameters of linear fitting function, this paper analyzes the significance of "training data", "label data" and "loss function" in machine learning, and shows how machine learning reduces the loss function, updates and optimizes the parameters through "gradient descent" algorithm, and finally obtains a reasonable linear fitting line (**Figure 1**).

Secondly, from the perspective of matrix multiplication, the construction idea from the input layer to the hidden layer and then to the output layer of neural network is analyzed (**Figure 2**). Taking the nonlinear data set as an example, the example of fitting the nonlinear function curve with the neural network machine model is shown, and the learning effects of neural networks with different "excitation functions" are also compared (**Figure 3**).

Then, the basic framework of convolution neural network for deep learning is analyzed, including the function of convolution kernel, the working process of convolution layer and pooling layer, and how the pooling layer is connected to ordinary neural network (**Figure 4**). Finally, it introduces how to build the prediction model of winter monthly temperature in East Asia through CMIP5 "big data" and convolutional neural network, and carry out the return test using the observed data (**Figure 5**, **Figure 6** and **Figure 7**). At the same time, the importance of building machine learning prediction model guided by climate dynamics knowledge is discussed (**Figure 8**, **Figure 9**).

It should be pointed out that machine learning is already a comprehensive discipline, including many algorithms, such as batch gradient descent method, random gradient descent method, small batch gradient descent method, linear regression, logical regression, decision tree, naive Bayes, k-proximity, learning vectorization, support vector machine, random forest, etc. Deep learning is only an important branch of machine learning. Its algorithms include convolutional neural network, cyclic neural network, generative countermeasure network and deep reinforcement learning. This paper only briefly introduces the batch gradient descent algorithm, shallow neural network and Convolution

Neural Network in machine learning, so as to preliminarily understand the principle and function of machine learning and provide some basic knowledge for further understanding of machine learning.

Conflict of interest

The authors declare that they have no conflict of interest.

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Original Research Article

Fractional Order Modeling of 1,2,3 DOF Robot Dynamic

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ABSTRACT

The fractional order modeling method of robot dynamics with one, two and three degrees of freedom is introduced. The stability of the fractional order model is proved by using the second-order Lyapunov method. A basic physical parameter is considered, that is, the inertial mass of the connecting rod. Freecad software is used for mechanical design. The dynamic models of 2-DOF and 3-DOF robots are established, and their motion trajectories are given in plane (x, y) and space (x, y, z) respectively. The model is programmed on the development card based on microcontroller. The advantage of the development card lies in its peripheral output, because it has two analog output channels, which are sent to the oscilloscope. The results are consistent with the proposed model.

Keywords: *Machine Translation; Deep Learning; Neural Machine Translation; Urdu Language; Chinese Language*

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1. Introduction

Mathematical model is the approximate value of physical system behavior. In the existing mathematical tools, fractional-order calculus (FOC) has interesting characteristics compared with integer order calculation. In the subject of system dynamics modeling, FOC has better approximation than integer order calculation. For example, FOC is applied to the modeling of diver system. The circuit dynamics model based on integer order differential equation shows the difference between the experimental data and the data generated by the model. The widely studied circuit is a circuit composed of resistance and capacitance in series. Due to the difference between integer order model data and experimental data, the model of the circuit is questioned. Gómez-Aguilar[1] proposed the fractional order model of RC circuit. The error of the data of the fractional order model is much smaller than that of the integer order model. Goodvine[2] introduced the application of FOC in the study of welding process dynamics. Tejado[3] applied FOC to the study of human arm, and Rosario[4] used FOC on the axis of robot arm. Shalaby[5] introduced an inverted pendulum into the FOC model. Zhang[6] introduced FOC when estimating the CARC state of supercapacitors. Shi et al.[7] proved that FOC based control can suppress interference, and Ceron-Morales[8] realizes the control of solar concentrator through FOC.

For robots that can be modeled with various technologies[9], one of the widely used robot modeling equations is Euler-Lagrange equation, and the result is an integer order differential equation system. The proposed fractional order model must first meet the stability conditions. If the fractional order model meets the stability requirements, it can be simulated and applied to practical purposes. Therefore, the stability proof using Lyapunov's second criterion is given.

It is difficult to apply fractional order modeling to the actual situation[10]. Therefore, this paper uses the development card to realize the fractional order modeling of one, two and three degree of freedom (DOF) robots, and reports the implementation of using multiple microcontrollers. Like the work of Flores-Ordeñana et al.[11], inwhich STM32 card is used for its built-in advantages[12,13].

This work is limited to showing the simulation results realized on the STM32L476 development card, because building a robot with the simplest design parameters requires financial investment, which cannot be realized at present.

2. Development

The robot connecting rod is a mechanical part, which has mechanical properties that must be determined digitally. As shown in the **Figure 1**, you can see a connecting rod designed in a free software called FreeCAD.

The mechanical parameters required for dynamic simulation are mass moment of inertia (also known as moment of inertia) and center of mass position. The parts must be solid materials and their bulk mass density must be known data (ρ). **Table 1** divides the connecting rod into four basic geometric figures and specifies the equations for calculating mass moment of inertia and center of mass.

The parallel axis theorem is used to calculate the moment of inertia mass of the combined graph. When calculating the moment of inertia mass of the complete graph, the moment of inertia of the hollow graph is negative. Use the equations in **Table 1** to design the connecting rod parameters, and take into account the materials with known mass bulk density. Then calculate the mass of mechanical components, and design the robot mechanism according to these known numerical values. The simplest is the single connecting rod mechanically coupled to the motor[14]. Taking the mechanism as the starting point, the dynamic model of the mechanism is established.

Considering the single degree of freedom manipulator (1DOF) diagram shown in **Figure 2**, parameters such as mass, length and moment of inertia are observed. These mechanical parameters and simulation values are shown in **Table 2**.

The first-order integer mathematical model is obtained by using Euler-Lagrange equation. The obtained dynamic model is (1):

$$\tau = (ml^2 + I)\ddot{q} + b\dot{q} + mgl_c\, sen(q) \tag{1}$$

The goal is to position the linkage at the desired (q_d) angle. (1) is written in the form of state variables (2) and (3):

$$\tilde{q} = q_d - q \tag{2}$$

$$\dot{q} = \frac{dq}{dt} \tag{3}$$

According to the state variables, the dynamic system is shown in (4):

$$\frac{d}{dt}\begin{bmatrix}\tilde{q}\\ \dot{q}\end{bmatrix} = \left[\left(ml^2 + I\right)^{-1}\left(\tau - bq - mgl_c\,\mathrm{sen}(q)\right)\right] \tag{4}$$

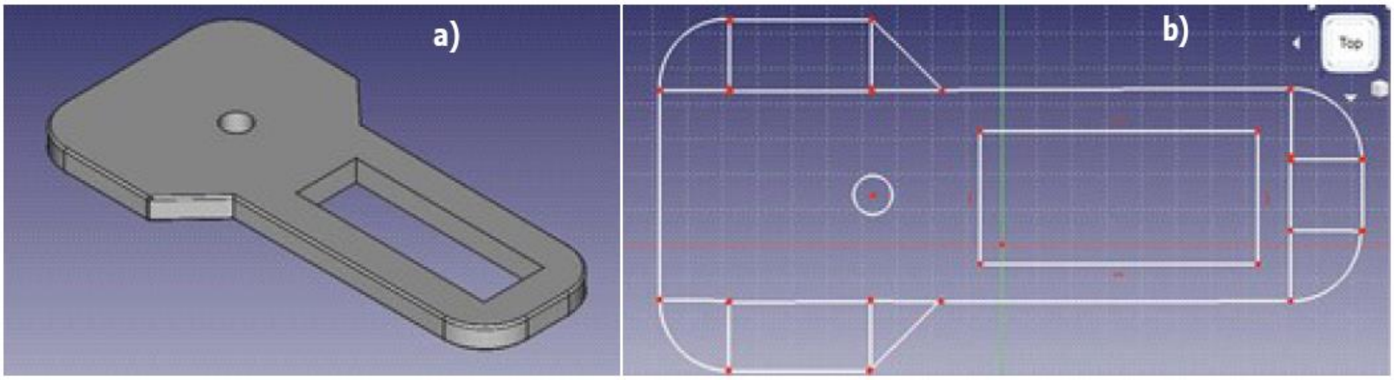
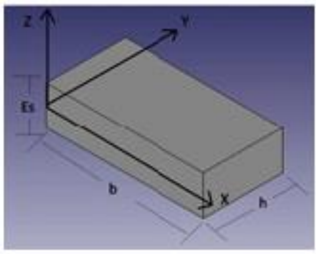
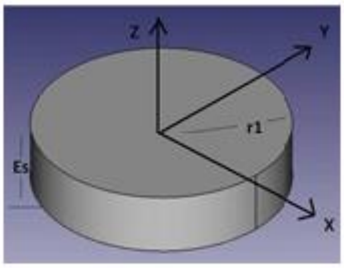
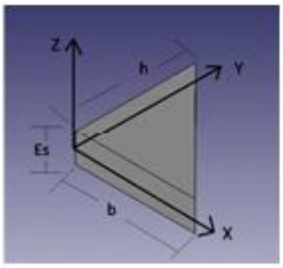
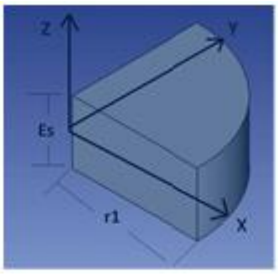


Figure 1. (a) Connecting rod design in FreeCAD; (b) dividing the connecting rod plane into basic geometric figures.

Table 1. An equation for calculating the basic parameters of the simple geometry constituting the robot connecting rod

Rectangular	Circular	Triangular	Bend
			
Mass moment of inertia			
$(\rho \cdot Es)\cdot\left[\frac{bh^3}{12}+\frac{b^3h}{12}\right]$	$\frac{r_1^2}{2}\cdot\left(\rho Es\pi r_1^2\right)$	$\left(\frac{4\rho Es}{3}\right)\left(\frac{bh}{2}\right)\left[h^2+b^2\right]$	$\frac{r_1^2}{8}\cdot\left(\rho Es\pi r_1^2\right)$
Centroid			
$\left(\frac{b}{2},\frac{h}{2},\frac{Es}{2}\right)$	$\left(0,0,\frac{Es}{2}\right)$	$\left(\frac{b}{3},\frac{h}{3},\frac{Es}{2}\right)$	$\left(\frac{4r_1}{3\pi},\frac{4r_1}{3\pi},\frac{Es}{2}\right)$

If expressed by Laplace transform, we get (5).

$$\begin{bmatrix} s\tilde{q} \\ s\dot{q} \end{bmatrix}=\begin{bmatrix} -\dot{q}(s) \\ \left(ml^2+I\right)^{-1}\left(\tau-b\dot{q}(s)-mgl_c\,\mathrm{sen}(q(s))\right) \end{bmatrix} \quad (5)$$

The integer derivative of the angular position function is represented by (6), and according to Krishna[2], the fractional derivative is (7).

$$\mathrm{L}\left\{\frac{dq(t)}{dt}\right\}=sq(s) \quad (6)$$

$$\mathrm{L}\left\{\frac{d^{\mu}q(t)}{dt^{\alpha}}\right\}=s^{\mu}q(s) \quad (7)$$

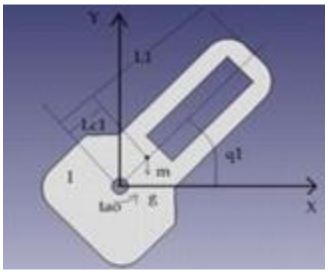


Figure 2. Connecting rod diagram of 1-DOF robot.

Equation (7) has an approximation of the quotient, which is the approximation of each continuous fraction in (8).

$$s^{\mu}q(s)\approx\frac{\mathrm{As}+1}{\mathrm{s}+\mathrm{A}} \quad (8)$$

Table 2. Physical parameters of one degree of freedom manipulator

Parameter	Link 1	Value	Unit
quality	m	1	kg .
length	L	1	m
Center length	LC company	0.5	m
quality			
Moment of inertia	I	0.1	$kg\cdot m^2$
Viscous friction coefficient	b	0	$N\cdot m\cdot s^{-1}$
Torsion	τ	-	N
Angular position	q	-	Grade
angular velocity	$\dot{q}$	-	$grade\cdot s^{-1}$
angular acceleration	$\ddot{q}$	-	$grade\cdot s^{-2}$

Conditions (9) and (10) must meet:

$$A=\frac{1+\mu}{1-\mu} \quad (9)$$

$$0<\mu<1 \quad (10)$$

Therefore, the fractional order approximation applied to model (5) is expressed as (11).

$$\begin{bmatrix} s^{\mu}\tilde{q} \\ s^{\mu}\dot{q} \end{bmatrix}=\begin{bmatrix} -\dot{q}(s) \\ \left(ml^2+I\right)^{-1}\left(\tau-b\dot{q}(s)-mgl_c\,\mathrm{sen}(q(s))\right) \end{bmatrix} \quad (11)$$

(12) is obtained by replacing (8) in (11).

$$\begin{bmatrix}(As+1)\tilde{q}\\(As+1)\dot{q}\end{bmatrix}=\begin{bmatrix}-(s+A)\dot{q}(s)\\\left(ml^2+I\right)^{-1}(S+A)\left(\tau-b\dot{q}(s)-mgl_c\operatorname{sen}(q(s))\right)\end{bmatrix}\tag{12}$$

On this point, a proportional derivative control (15) plus gravity compensation in (13) is proposed. It is worth mentioning that PD control has neural network versions[12,16].

$$\tau=k_p\tilde{q}-k_v\dot{q}(s)+mgl_c\operatorname{sen}(q(s))\tag{13}$$

By replacing (13) with (12) and executing the algebra shown, a compact equation can be obtained, with is supported by the variables shown in (14), (15), (16) and (17). Using the inverse Laplace transform, the result is (18).

$$A_{11}=\frac{A^3\left(ml^2+I\right)+A^2\left(k_v+b\right)+Ak_p}{A^2\left(ml^2+I\right)+A\left(k_v+b\right)+k_p}\tag{14}$$

$$A_{12}=\frac{1-A}{A}\tag{15}$$

$$A_{21}=\frac{k_pA(1-A)}{A^2\left(ml^2+I\right)+A\left(k_v+b\right)+k_p}\tag{16}$$

$$A_{22}=\frac{A^2\left(k_v+b\right)+A\left(ml^2+I+k_p\right)}{A^2\left(ml^2+I\right)+A\left(k_v+b\right)+k_p}\tag{17}$$

$$\frac{d}{dt}\begin{bmatrix}\tilde{q}\\\dot{q}\end{bmatrix}=\begin{bmatrix}-A_{11}\tilde{q}+A_{12}\dot{q}\\A_{21}\tilde{q}-A_{22}\dot{q}\end{bmatrix}\tag{18}$$

At this point, a candidate Lyapunov function (19) is proposed.

$$V(\tilde{q},\dot{q})=\frac{1}{2}k_1\tilde{q}^2+\frac{1}{2}k_2\dot{q}^2\tag{19}$$

It is deduced that the candidate Lyapunov function about time is (20).

$$\frac{d}{dt}V(\tilde{q},\dot{q})=k_1\tilde{q}\frac{d\tilde{q}}{dt}+k_2\dot{q}\frac{d\dot{q}}{dt}\tag{20}$$

(21) is obtained by substituting (18) into (20) and performing algebraic operations.

$$\frac{d}{dt}V(\tilde{q},\dot{q})=-CAk_1\tilde{q}^2-CDk_2\dot{q}^2-(A-1)\left(k_1+k_2k_pA^2\right)\tilde{q}\dot{q}\le 0\tag{21}$$

The support (21) is considered to be (22).

$$\frac{d}{dt}V(\tilde{q},\dot{q})\le-\left(\left(A_{11}k_1\right)^{\frac{1}{2}}\tilde{q}+\left(A_{22}k_2\right)^{\frac{1}{2}}\dot{q}\right)^2\tag{22}$$

By developing the algebra shown in (22), result (23) completes the proof of Lyapunov stability of fractional order model.

$$-(A-1)\left(k_1+k_2k_pA^2\right)\tilde{q}\dot{q}\le$$
$$\le\sqrt{\left(k_1A^3\left(ml^2+I\right)+k_1A^2\left(k_v+b\right)+k_1A^2k_p\right)}$$
$$\sqrt{\left(k_2A\left(A^2\left(k_v+b\right)+A\left(ml^2+I+k_p\right)\right)\right)}\tilde{q}\dot{q}\tag{23}$$

The proof given shows that the equilibrium point of the new model is represented by (24).

$$\begin{bmatrix}\tilde{q}\\\dot{q}\end{bmatrix}=\begin{bmatrix}0\\0\end{bmatrix}\Bigg|_{t\to\infty}\tag{24}$$

The simulation results show that it is feasible to use the fractional order model for stability simulation, that is, the equations can be written in programming language, and the dynamic behavior of 1 DOF manipulator is simulated, (24) shows that the model has convergence. The simulation will be introduced later, and continue to introduce the modeling of 2 and 3 DOF robots. **Figure 3** shows a 2 DOF robot in which two connecting rods move on a plane.

The physical parameters of 2 DOF robot are shown in **Table 3**. The Euler-Lagrange model of robot 2 DOF is shown in (25)

$$\begin{bmatrix}\tau_1\\\tau_2\end{bmatrix}=\begin{bmatrix}m_{11}(q)&m_{12}(q)\\m_{21}(q)&m_{22}(q)\end{bmatrix}\begin{bmatrix}\ddot{q}_1\\\dot{q}_2\end{bmatrix}+\begin{bmatrix}b_1&0\\0&b_2\end{bmatrix}\begin{bmatrix}\dot{q}_1\\\dot{q}_2\end{bmatrix}+$$
$$+\begin{bmatrix}c_{11}(q,\dot{q})&c_{12}(q,\dot{q})\\c_{21}(q,\dot{q})&c_{22}(q,\dot{q})\end{bmatrix}\begin{bmatrix}\dot{q}_1\\\dot{q}_2\end{bmatrix}+\begin{bmatrix}g_1(q)\\g_2(q)\end{bmatrix}\tag{25}$$

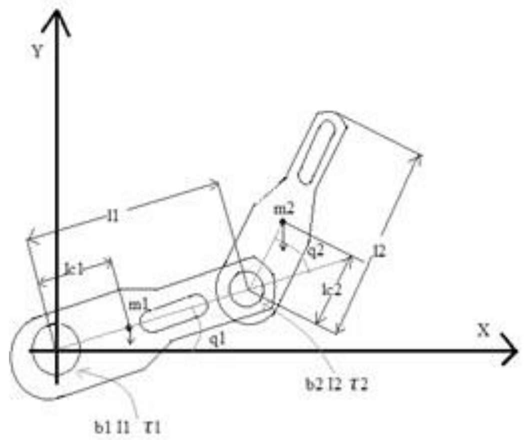


Figure 3. Schematic diagram of 2-DOF robot.

According to the physical parameters, the equation of the matrix element is shown between (26) and (35).

$$m_{11}(q) = m_1 lc_1^2 + m_2 lc_2^2 + I_1 + I_2 + 2m_2 l_1 lc_2 \cos(q_2) \tag{26}$$

$$m_{12}(q) = m_2 lc_2^2 + I_2 + m_2 l_1 lc_2 \cos(q_2) \tag{27}$$

$$m_{12}(q) = m_2 lc_2^2 + I_2 + m_2 l_1 lc_2 \cos(q_2) \tag{28}$$

Table 3. Physical parameters of 2-DOF manipulator

Parameter	Link 1	Link 2	Unit
quality	m_1	m_2	kg
	0.1	0.05	
length	L_1	L_2	m
	0.1	0.1	
Center length quality	Lc_1 0.05	Lc_2 0.05	m
Moment of inertia	I_1	I_2	kg·m^2
	0.2	0.09	
friction coefficient	b1	b2	N·m·s^{-1}
Viscous	0.2	0.17	
Torsion	$\tau 1$	$\tau 2$	N
Angular position	q_1	q_2	Grade
angular velocity	$\dot{q}_1$	$\dot{q}_2$	grade·s^{-1}
angular acceleration	$\ddot{q}_1$	$\ddot{q}_2$	grade·s^{-2}

$$m_{22}(q) = m_2 lc_2^2 + I_2 \tag{29}$$

Due to the symmetry of matrices and M (27) and (28), they are the same.

This C matrix, also known as the Coriolis matrix, represents terms (30) to (33). When an object moves to another rotating object, the Coriolis effect appears, which is why q_2 angle is an important dependency.

$$c_{11}(q) = -2m_2 l_1 lc_2 \dot{q}_2 \sin(q_2) n \tag{30}$$

$$c_{12}(q) = -m_2 l_1 lc_2 q_2 \sin(q_2) \tag{31}$$

$$c_{21}(q) = m_2 l_1 lc_2 q_1 \sin(q_2) \tag{32}$$

$$c_{22}(q) = 0 \tag{33}$$

The term due to gravity is given in (34) and (35).

$$g_1(q) = m_1 g lc_1 \sin(q_1) + m_2 g l_1 \sin(q_1) + m_2 g lc_2 \sin(q_1 + q_2) \tag{34}$$

$$g_2(q) = m_2 g lc_2 \sin(q_1 + q_2) \tag{35}$$

The model is processed according to the state variables (36) to (39) and the substitution (40) in (25) is obtained.

$$q_1 = x_1 \tag{36}$$

$$q_2 = x_3 \tag{37}$$

$$\dot{q}_1 = x_2 = \dot{x}_1 \tag{38}$$

$$\dot{q}_2 = x_4 = \dot{x}_2 \tag{39}$$

To present a compact representation, (41) is used to simplify the matrix.

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_3 \\ \dot{x}_2 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_2 \\ x_4 \end{bmatrix} \\ \begin{bmatrix} m_{11}^{-1}(x) & m_{12}^{-1}(x) \\ m_{21}^{-1}(x) & m_{22}^{-1}(x) \end{bmatrix} \begin{Bmatrix} f_1 \\ f_2 \end{Bmatrix} \end{bmatrix} \tag{40}$$

$$\begin{bmatrix} f_1 \\ f_2 \end{bmatrix} = \left\{ \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} - \begin{bmatrix} c_{11}(x) & c_{12}(x) \\ c_{21}(x) & c_{22}(x) \end{bmatrix} \begin{bmatrix} x_3 \\ x_4 \end{bmatrix} - \begin{bmatrix} b_1 & 0 \\ 0 & b_2 \end{bmatrix} \begin{bmatrix} x_3 \\ x_4 \end{bmatrix} - \begin{bmatrix} g_1(x) \\ g_2(x) \end{bmatrix} \right\} \tag{41}$$

At this point, we develop algebra and further simplify it with (42) and (43).

$$G_1 = m_{11}^{-1} f_1 + m_{12}^{-1} f_2 \tag{42}$$

$$G_2 = m_{21}^{-1} f_1 + m_{22}^{-1} f_2 \tag{43}$$

As with the single link system, the fractional order approximation (44) is applied, and a program similar to the 1 DOF robot is used to finally obtain the fractional order model shown in (45).

$$\begin{bmatrix} s^{\mu}x_1 \\ s^{\mu}x_2 \\ s^{\mu}x_3 \\ s^{\mu}x_4 \end{bmatrix} = \begin{bmatrix} x_2 \\ G_1 \\ x_4 \\ G_2 \end{bmatrix} \tag{44}$$

In (44), the approximation shown in (12) is performed, and algebra and simplification terms are performed. Finally, the fractional order model of 2 DOF robot is established.

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} \left(\frac{T}{A^2}\right)\dot{G}_1 + \frac{T}{A}G_1 + T\left(\frac{A^2-1}{A^2}\right)x_{2t} + x_{1t}\left(1-\frac{T}{A}\right) \\ \left(\frac{T}{A}\right)\dot{G}_1 + TG_1 + x_{2t}\left(1-\frac{T}{A}\right) \\ A_2 + \frac{T}{A}G_2 + T\left(\frac{A^2-1}{A^2}\right)x_{4t} + x_{3t}\left(1-\frac{T}{A}\right) \\ \left(\frac{T}{A}\right)\dot{G}_2 + TG_2 + x_{4t}\left(1-\frac{T}{A}\right) \end{bmatrix} \tag{45}$$

In (45), I = 1 $i = 2$ until.

$$\dot{G}_i \approx \frac{G_i(t-T) - G_i(t-2T)}{T} \tag{46}$$

Arrangements similar to (18) could have been proposed, but in this case $(A_{11}, A_{12}, A_{21}, A_{22})$ would be a matrix.

Finally, the fractional order model of 3 DOF robot is given, and its modeling scheme is shown in the **Figure 4**. The 3 DOF robot model in the reference dose not meet the requirements in **Figure 4.** Therefore, the modeling is carried out step by step from direct kinematics, inverse kinematics and Euler-Lagrange, and the calculation is repeated to check the error. Once the correct equation is obtained, the parameters given in **Table 4** are applied.

For 3 DOF robot, the Euler-Lagrange model shown in (47) is taken as the starting point.

$$\begin{bmatrix} \ddot{q}_1 \\ \ddot{q}_2 \\ \ddot{q}_3 \end{bmatrix} = \begin{bmatrix} i_{11} & i_{12} & i_{13} \\ i_{21} & i_{22} & i_{23} \\ i_{31} & i_{32} & i_{33} \end{bmatrix} \left\{ \begin{bmatrix} \tau_1 \\ \tau_2 \\ \tau_3 \end{bmatrix} - \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \begin{bmatrix} \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix} - \begin{bmatrix} b_1\dot{q}_1 \\ b_2\dot{q}_2 \\ b_3\dot{q}_3 \end{bmatrix} - \begin{bmatrix} g_1 \\ g_2 \\ g_3 \end{bmatrix} \right\} \tag{47}$$

In equation (47), the inverse matrix I is (48):

$$\begin{bmatrix} i_{11} & i_{12} & i_{13} \\ i_{21} & i_{22} & i_{23} \\ i_{31} & i_{32} & i_{33} \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{bmatrix}^{-1}$$

$$= \frac{1}{\Delta}\begin{bmatrix} m_{22}m_{33} - m_{23}m_{32} & m_{13}m_{32} - m_{12}m_{33} & m_{12}m_{23} - m_{13}m_{22} \\ m_{23}m_{31} - m_{21}m_{33} & m_{11}m_{33} - m_{13}m_{31} & m_{13}m_{21} - m_{11}m_{23} \\ m_{21}m_{32} - m_{22}m_{31} & m_{12}m_{31} - m_{11}m_{32} & m_{11}m_{22} - m_{12}m_{21} \end{bmatrix} \tag{48}$$

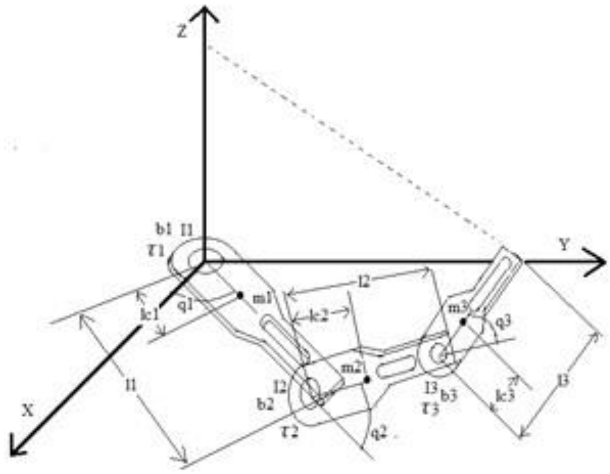


Figure 4. Schematic diagram of three degree of freedom robot.

As determinant (49);

$$\Delta = m_{11}\left(m_{22}m_{33} - m_{23}m_{32}\right) + m_{12}\left(m_{23}m_{31} - m_{21}m_{33}\right) +$$
$$+m_{13}\left(m_{21}m_{32} - m_{22}m_{31}\right) \tag{49}$$

From (50) to (67), each element of the matrix is represented by physical parameters. Due to the symmetry of the *M* matrix, some terms of the matrix are equal, as shown in (51), (52) and (54).

$$m_{11} = m_1 ll_1^2 + I_1 + m_2 l_1^2 + 2m_3 l_1 l_2 \cos(q_2) + m_2 l_2^2 \cos^2(q_2) + I_2 + m_3 l_1^2$$
$$+2m_3 l_1 l_2 \cos(q_2) + 2m_3 l_1 lc_3 \cos(q_2 + q_3) + m_3 l_2^2 \cos^2(q_2)$$
$$+2m_3 l_2 lc_3 \cos(q_2)\cos(q_2 + q_3) + m_3 lc_3^2 \cos^2(q_2 + q_3) + I_3 \tag{50}$$

$$m_{12} = m_{21} = I_2 + I_3 \tag{51}$$

$$m_{13} = m_{31} = I_3 \tag{52}$$

$$m_{22} = m_2 lc_2^2 + m_3 l_2^2 + m_3 lc_1^2 + I_2 + I_3 + 2m_3 l_2 lc_3 \cos(q_3) \tag{53}$$

$$m_{23} = m_{32} = I_3 + m_3 l l_2 l c_3 \cos(q_3) + m_3 l c_3^2 \tag{54}$$

$$m_{33} = I_3 + m_3 l c_3^{\ 2} \tag{55}$$

Table 4. Physical parameters of three degree of freedom manipulator

Parameter	Link 1	Link 2	Link 3	Unit
Quality	m_1 19.5	m_2 1.3	m_3 1.1	kg
Length	L_1 1.2	L_2 1.1	L_3 1.1	m
Centroid length	lc_1 0.5	lc_2 0.5	lc_3 0.5	m
Moment of inertia	I_1 4.15	I_2 0.37	I_3 0.271	kg·m^2
Viscous friction coeffi-cient	b1 1.8	b2 1.8	b3 1.8	N·m·s^{-1}
Torsion	τ1	τ2	τ3	N
Angular position	q_1	q_2	q_3	Grade
Angular velocity	$\dot{q}_1$	$\dot{q}_2$	$\dot{q}_3$	grade·s^{-1}
Accelerate angular	$\ddot{q}_1$	$\ddot{q}_2$	$\ddot{q}_3$	grade·s^{-2}

The Coriolis matrix of 3 DOF robot represents the dependence of angular position q2 and q3, and there is no equal term in this matrix.

$$\begin{aligned} c_{11} &= -2m_2 l_1 l_2 \dot{q}_2 \operatorname{sen}(q_2) - 2m_2 l_2^{\ 2} \dot{q}_2 \cos(q_2)\operatorname{sen}(q_2) \\ &-2m_3 l_1 l_2 \dot{q}_2 \operatorname{sen}(q_2) - 2m_3 l_1 l c_3 \dot{q}_2 \operatorname{sen}(q_2+q_3) \end{aligned} \tag{56}$$

$$\begin{aligned} c_{12} &= -2m_3 l_2^{\ 2} \dot{q}_1 \cos(q_2)\operatorname{sen}(q_2) \\ &-2m_3 l_2 l c_3 q_1 \cos(q_2)\operatorname{sen}(q_2+q_3) \\ &-2m_3 l c_3^{\ 2} \dot{q}_1 \cos(q_2+q_3)\operatorname{sen}(q_2+q_3) \end{aligned} \tag{57}$$

$$\begin{aligned} c_{13} &= -2m_3 l_1 l c_3 \dot{q}_1 \operatorname{sen}(q_2+q_3) \\ &-2m_3 l_2 l c_3 \dot{q}_1 \operatorname{sen}(q_2+q_3)\cos(q_2) \\ &-2m_3 l c_3^{\ 2} \dot{q}_1 \cos(q_2+q_3)\operatorname{sen}(q_2+q_3) \end{aligned} \tag{58}$$

$$\begin{aligned} c_{21} &= m_3 l_1 l_2 \dot{q}_1 \operatorname{sen}(q_2) + m_3 l_1 l_3 \dot{q}_1 \operatorname{sen}(q_2+q_3) \\ &+ m_3 l_2^2 \dot{q}_1 \cos(q_2)\operatorname{sen}(q_2) + 2m_3 l_2 l c_3 \dot{q}_1 \cos(q_2)\operatorname{sen}(q_2+q_3) \\ &+ 2m_3 l_2 l c_3 \dot{q}_1 \operatorname{sen}(q_2)\cos(q_2+q_3) \\ &+ 2m_3 l_3^{\ 2} \dot{q}_1 \cos(q_2+q_3)\operatorname{sen}(q_2+q_3) \end{aligned} \tag{59}$$

$$c_{22} = -2m_3 l_2 l c_3 \dot{q}_3 \operatorname{sen}(q_3) \tag{60}$$

$$c_{23} = -m_3 l_2 l c_3 \dot{q}_3 \operatorname{sen}(q_3) \tag{61}$$

$$\begin{aligned} c_{31} &= m_3 l_1 l c_3 \dot{q}_1 \operatorname{sen}(q_2+q_3) \\ &+ m_3 l_2 l c_3 \dot{q}_1 \cos(q_2)\operatorname{sen}(q_2+q_3) \\ &+ m_3 l c_3^{22} q_1 \cos(q_2+q_3)\operatorname{sen}(q_2+q_3) \end{aligned} \tag{62}$$

$$c_{32} = -m_3 l_2 l c_3 \dot{q}_3 \operatorname{sen}(q_3) \tag{63}$$

$$c_{33} = m_3 l_2 l c_3 \dot{q}_2 \operatorname{sen}(q_3) \tag{64}$$

The terms related to gravity are given in sections 2 and 3. In section 1, since gravity is parallel to the earth's surface, there is no dependence on gravity.

$$g_1 = 0 \tag{65}$$

$$g_2 = m_2 g l c_2 \cos(q_2) + m_3 g l_2 \cos(q_2) + m_3 g l c_3 \cos(q_2+q_3) \tag{66}$$

$$g_3 = m_3 g l c_3 \cos(q_2+q_3) \tag{67}$$

Using the same method for 1 and 2 DOF system, the fractional dynamic model of 3 DOF robot is (68):

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix} = \begin{bmatrix} \left(\frac{T}{A^2}\right)\dot{G}_1 + \frac{T}{A}G_1 + T\left(\frac{A^2-1}{A^2}\right)x_{4t} + x_{1t}\left(1-\frac{T}{A}\right) \\ \left(\frac{T}{A^2}\right)\dot{G}_2 + \frac{T}{A}G_2 + T\left(\frac{A^2-1}{A^2}\right)x_{5t} + x_{2t}\left(1-\frac{T}{A}\right) \\ \left(\frac{T}{A^2}\right)\dot{G}_3 + \frac{T}{A}G_3 + T\left(\frac{A^2-1}{A^2}\right)x_{6t} + x_{3t}\left(1-\frac{T}{A}\right) \\ \left(\frac{T}{A}\right)G_1 + TG_1 + x_{4t}\left(1-\frac{T}{A}\right) \\ \left(\frac{T}{A}\right)\dot{G}_2 + TG_2 + x_{5t}\left(1-\frac{T}{A}\right) \\ \left(\frac{T}{A}\right)\dot{G}_3 + TG_3 + x_{6t}\left(1-\frac{T}{A}\right) \end{bmatrix} \quad (68)$$

(68) applies to (69) and (70):

$$\begin{bmatrix} G_1 \\ G_2 \\ G_3 \end{bmatrix} = \begin{bmatrix} i_{11} & i_{12} & i_{13} \\ i_{21} & i_{22} & i_{23} \\ i_{31} & i_{32} & i_{33} \end{bmatrix}$$

$$\left\{\begin{bmatrix} kp_1(q_{d1}-q_1) - kv_1\dot{q}_1 - c_{11}\dot{q}_1 - c_{12}\dot{q}_2 - c_{13}\dot{q}_3 - b_1\dot{q}_1 \\ kp_1(q_{d2}-q_2) - kv_2\dot{q}_2 - c_{21}\dot{q}_1 - c_{22}\dot{q}_2 - c_{23}\dot{q}_3 - b_2\dot{q}_2 \\ kp_1(q_{d3}-q_3) - kv_3\dot{q}_3 - c_{31}\dot{q}_1 - c_{32}\dot{q}_2 - c_{33}\dot{q}_3 - b_3\dot{q}_3 \end{bmatrix}\right\} \quad (69)$$

$$\begin{bmatrix} \dot{G}_1 \\ \dot{G}_2 \\ \dot{G}_3 \end{bmatrix} \approx \begin{bmatrix} \frac{G_1 - G_{1\_t}}{T} \\ \frac{G_2 - G_{2\_t}}{T} \\ \frac{G_3 - G_{3\_t}}{T} \end{bmatrix} \quad (70)$$

3. Result

This section compares the integer order model with the model developed using FOC. **Figure 5** shows the response diagram of the first-order integer and second-order fractional robot connecting rod, and the order of the fractional derivative is $\mu = 0.99$ and $\mu = 0.95$. The very similar diagram shows that the steady-state error is more obvious for the fractional order model. If the value of μ is small, this is what we want to prove. The velocity diagram of link 1 also shows that the velocity approaches zero, i.e. the equilibrium value is reached. As shown in the **Figure 5**, the fractional order response is slower than the integer order model. In fact, if the fractional order model with high response speed is to be simulated, the continuous fractional approximation (8) must have more terms. The more terms, the more accurate the bandwidth of the fractional order model[9]. Finally, in this simulation, the q_1 required angle is 90° .

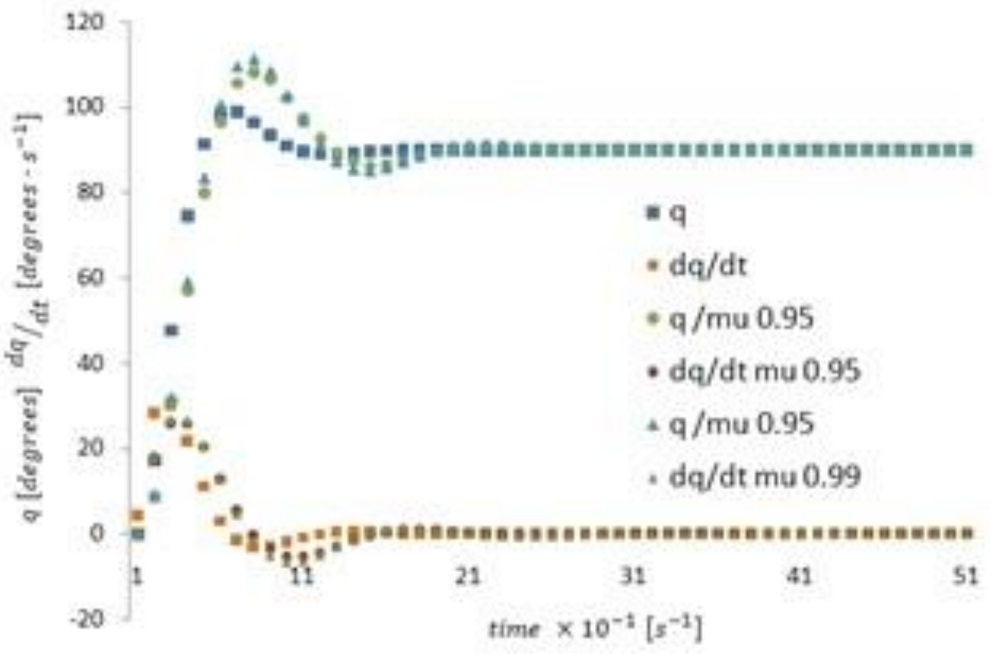


Figure 5. Graphical response of the 1 DOF robot.

Figure 6 shows the response diagram of connecting rod 1 of the 2 DOF robot, which is of integer order and two fractional orders, and the order of the fractional derivative is $\mu = 0.99$ and $\mu = 0.95$. The fractional order diagram shows that the error in the steady state is easier to observe, and the speed approaches zero, i.e. it reaches the equilibrium value. In the simulation, the q_1 and q_2 required angle is 10°.

Figure 7 shows the response diagram of the connecting rod 1 of the 3 DOF robot, which is of integer order and two fractional orders, and the fractional derivative is $\mu = 0.99$ and $\mu = 0.95$. The fractional order diagram shows that the error in the steady state is easier to observe, and the speed approaches zero, i.e. it reaches the equilibrium value. In the simulation, the q_1, q_2 and q_3 required angle is 5° in the graphics of 3 DOF robot.

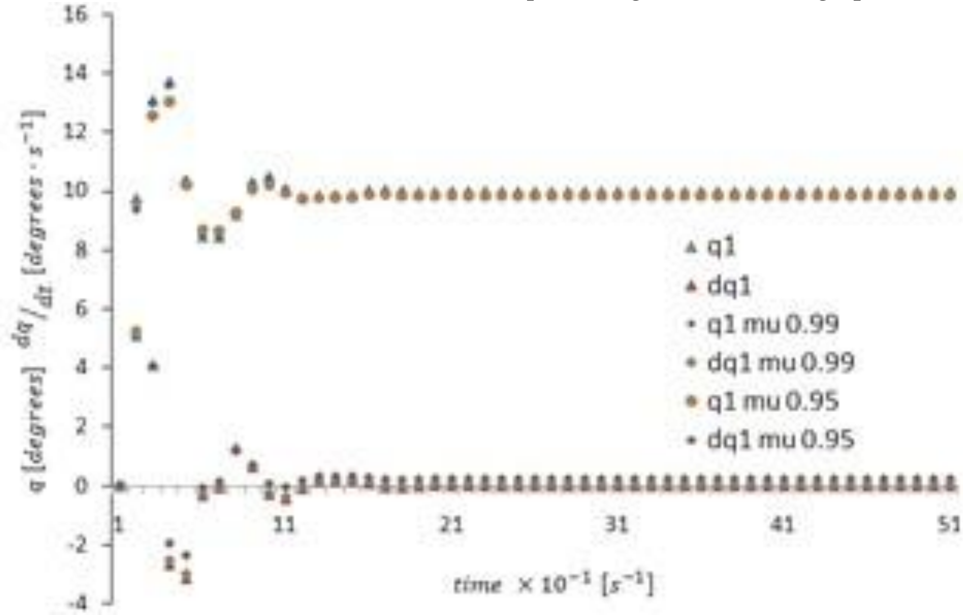


Figure 6. Response diagram of connecting rod 1 of the 2 DOF robot.

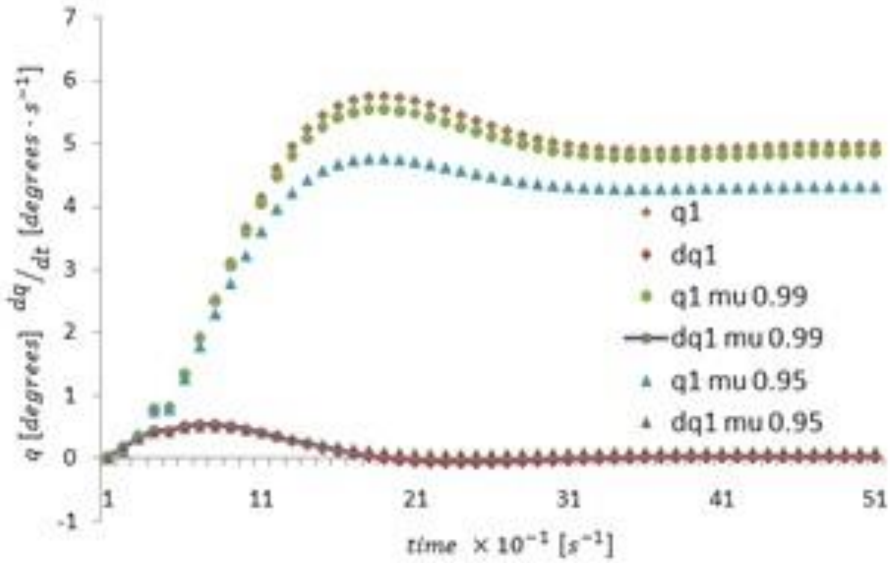


Figure 7. Response diagram of connecting rod 1 of the 3 DOF robot.

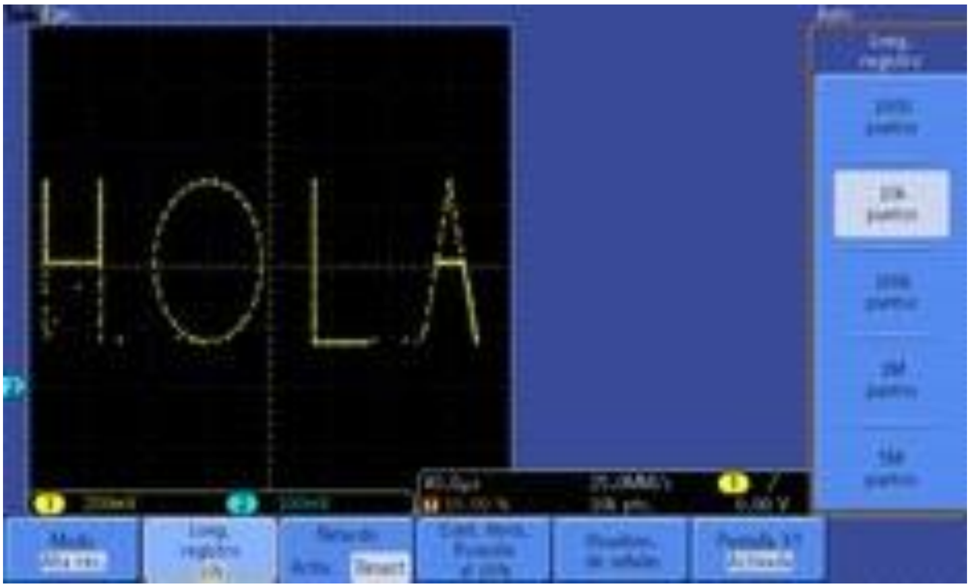


Figure 8. Output the image of “HOLA” track on the oscilloscope.

Figure 9. The figure shows the “HOLA Dr CHUA” track output by the oscilloscope.

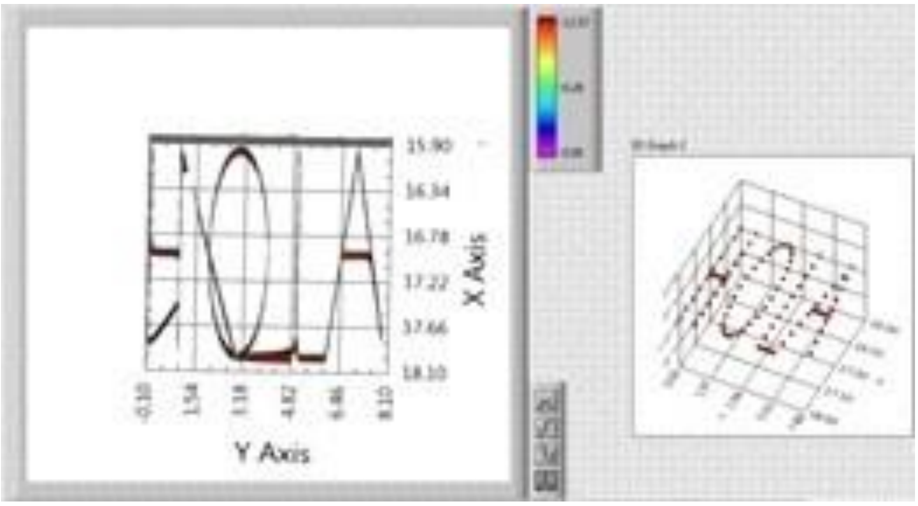


Figure 10. Set the “HOLA” path for the score model of 3 DOF in LabVIEW.

Within the application scope of these models, the trajectories of 2 and 3 DOF models and "H" "O" "L" "A" are designed by using the advantages of STM32L476 card. In the case of 2 DOF model, the route is drawn by oscilloscope, as shown in the **Figure 8**. In addition, a path of "HOLA Dr CHUA" is designed and displayed on the oscilloscope. For the 3 DOF model, the "HOLA " track is drawn in LabVIEW, as shown in **Figure 10**.

Figures 8 and **9** are obtained using Tektronix DPO3032 oscilloscope. Photos of greetings to the head of ITSPR are shown in the **Figure 9**.

4. Conclusion

The results show that the fractional order modeling of the dynamic model of the rotating manipulator will produce convergence results when it is expected to reach a certain position or describe a trajectory in the point-to-point control method. In fact, the fractional order must be close to the first order, which shows that the difference between the traditional integer order model and the fractional order model is not significant. The fractional order model includes the following points.

1. The results show that the fractional order dynamic model meets the second criterion of Lyapunov stability, which shows that the model has convergence.

2. The simulation diagram shows the expected error of the fractional order model in the steady state, which means that the fractional order model is more accurate than the integer order model.

3. The fractional order model allows to simulate the complex trajectories of 2 and 3 DOF systems, which are implemented on STM32L476 development card and displayed on oscilloscope.

Conflict of interest

None declared./The authors declare that they have no conflict of interest.

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Original Research Article

The Implementation of Hexagonal Robot Mapping and Positioning System Focuses on Environmental Scanning and Temperature Monitoring

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ABSTRACT

Various researches in the field of robotics have made great progress in developing methods to effectively determine the position of robots in unknown environments. The simultaneous localization and mapping (SLAM) task make determining the current position of the robot and performing path mapping possible. In this mapping, solid elements (landmarks) existing in the actual environment are even detected, which indicate that the direction of the robot changes during walking. This scheme provides the implementation analysis of the probabilistic particle filter method, which ensures the correct performance in the controlled actual scene under specific conditions, obtains the non-network connection environment information by storing the data in the temperature value sampling in the CVS file, and monitors the temperature measurement by displaying the heat map. Successful analysis must ensure the robustness of the results obtained when implementing these systems and take into account the feasibility of applying this work to the proposed objectivesd.

Keywords: *Particle Filter; Temperature; Position; Sampling; Mapping; Hexagonal Robot*

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1. Introduction

Exploration has always been a necessary activity in order to be able to learn the characteristics of our surrounding environment, which even needs to enter areas where the environment may pose a risk to humans[1]; now, robot technology enables us to achieve this goal at such an advanced level that it is possible for us to develop autonomous navigation algorithms and sample different environmental variables through temperature, humidity, pressure and other sensors[2]; the localization and mapping of mobile robot applications can help to determine the location in the region in some unknown cases, which can be realized by developing heuristic methods[3], which makes the autonomous navigation problem have a new vision with the development of SLAM (simultaneous localization and mapping).

Through the research and application of various mapping and positioning methods[4], we can obtain automata robots, which can complete more complex work for human beings by reducing execution time and improving execution efficiency[5]. The application of the system requires the use of sensors[2] that can interact with the surrounding environment to generate noise in the measurement process, resulting in a certain degree of error in the measurement results. Similarly, in order to obtain environmental data, the values extracted by the temperature and humidity sensors must be stored through the offline data acquisition of the robot once the robot establishes a reliable network connection, it can extract this information remotely and draws a two-dimensional temperature and location map to better analyze the scanning results.

Apart from the automation of the robot, another premise is the fact that the autonomous robot can explore inaccessible areas which requires a technology that can identify the scanned area and create a map to help it determine the appropriate route during walking. It is possible through the use of simultaneous positioning and mapping (SLAM)[4] algorithm, which is helpful to develop various applications. In this special case, the particle filter method is used to create the environment map, reduce the possibility of equipment crossing the boundary, and collect as much information as possible from the scanning area. **Figure 1** shows the detection of landmarks or reference points which are represented by orange points captured by the robot to bypass the obstacle. Green represents the scattering of the resampled particles, magenta the original particles, and the robot is represented by a blue circle that displays its direction through the position vector.

It is important to consider that the stability of the robot used[6] which must have sufficient robustness in its structure, as well as the appropriate strategy of the system required for integrated scanning and the amount of memory stored and the type of processing equipment of the system. Therefore, the purpose of this analysis is to establish the appropriate parameters of the particle filter suitable for the hexagonal robot, and to determine the strategy used to generate the temperature map by using the temperature and position data storage system, so as to re sample the scanning area using low-cost equipment such as DHT-11.

2. Overview of scanning system

The scanning system proposed in this paper consists of two important stages with which we want to make an analysis of the application of SLAM[7] and data acquisition on the ezrobot[6] hexapod robot model. The specific steps are as follows:

Simultaneous positioning and mapping. The task of this stage is to guide the robot through a limited test environment whose landmarks have been preset. This process is completed in Python using Raspberry Pi 3B card[8].

Temperature data acquisition. Through the DHT-11 sensor, the temperature variables collected during the whole scanning process are sampled. These temperature variables are stored in the CVS file for subsequent reading and downloading to the computer, which maintains a wireless connection with the Raspberry Pi card installed on the robot. **Figure 2** shows the basic structure and operation realized on the hexagonal robot.

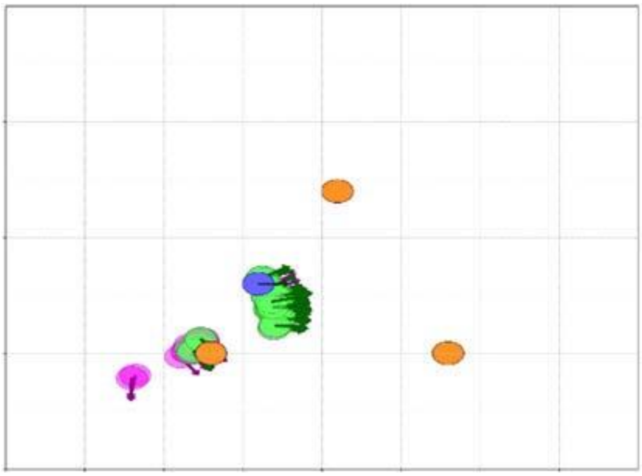

Figure 1. Robots detect landmarks.

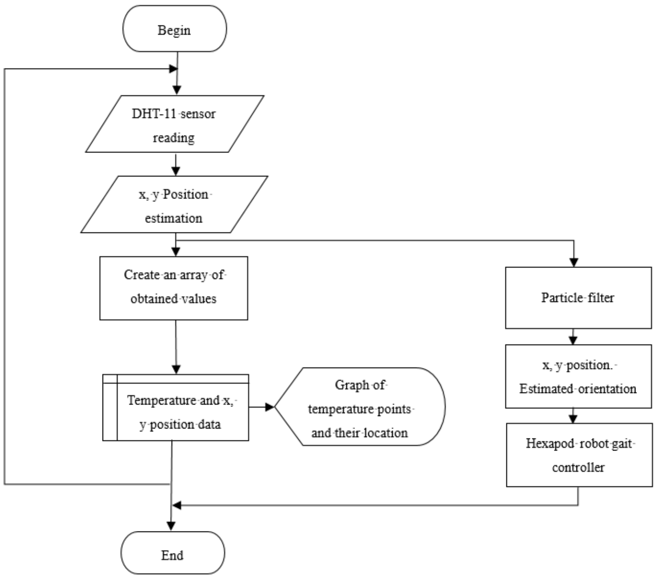

Figure 2. Overall flow chart

2.1 Particulate filter

This filter is obtained by replacing the appropriate probabilistic motion and perception model in the particle filter algorithm. It represents that the belief consists of a group of particles

$$Mxt = \left\{x_t^{[1]}, x_t^{[2]}, \ldots, x_t^{[M]}\right\}. \tag{1}$$

The measurement model is applied to on-line measurement of particle weight. The initial belief bel $(x0)$ is obtained by randomly generating M particles from the previous distribution $p(x0)$ mathrmy and assigning a uniform importance factor $M-1$ to each particle.

The algorithm is simple to implement and suitable for scene location based on reference points.

A common strategy for establishing M is to keep sampling until the next one reaches ut and zt. In this way, the implementation is adaptive to computing resources: the faster the underlying processor, the better the positioning algorithm. However, care should be taken to ensure that the number of particles remains high enough to avoid filter divergence. The filter has the characteristics of non-parametric approximation that can represent complex multimode probability distribution, and is perfectly combined with Gaussian central distribution. When you get this position, particles elsewhere may not disappear. In some cases, particles only "survive" near a single pose. If this pose is proved to be wrong, the algorithm cannot recover.

This problem can be solved by a heuristic algorithm, which includes injecting random particles, which can be mathematically adjusted under the assumption that the robot may be hijacked with a small probability, so as to generate the score of random state in the motion model. However, even if the robot is not hijacked, random particles will add additional robustness. One way to realize this idea is to monitor the probability of sensor measurement:

$$p\left(Z_t \mid Z_{1:t-1}, u_{1:t^p} m\right) \tag{2}$$

And link each method to the possibility of measurement (provided according to the data). In the particle filter, the approximate value of this quantity is easily obtained from the importance factor, because according to the definition, the importance weight is a random estimation of this probability. Average:

$$\frac{1}{M}\sum_{m=1}^{M}\omega_t^{[m]} \sim p\left(Z_t \mid Z_{1:t-1}, u_{1:t} m\right) \tag{3}$$

Usually, it's a good idea to smooth this estimate by averaging a few time steps. In addition to fault location, there are many reasons why the measurement probability may be very low. The noise level of the sensor may be abnormally high, or the particles may be dispersed in the global positioning stage. For these reasons, when determining the number of random samples, it is best to maintain the short-term average of the measurement probability and link it with the long-term average[3].

2.2 Temperature mapping

The data acquisition system obtained by the scanning robot from the environment represents one of the most important applications for sampling in various research fields. Various works related to this application[9,10] focus on communication and real-time data visualization. The data is related to the sampling time. However, in the scanning stage, when it is carried out in the area with some signal interference, the communication between devices becomes complex. Through experimental research, this paper analyzes the method of correcting the sensor name by using DHT-11 temperature sensor and Raspberry Pi 3B processing card to realize off-line data acquisition and graphical representation of sampling point position.

When sampling, the lowest and highest temperature values that the hexagonal robot material may be exposed to shall be regarded as the main conditions. Its structure is composed of a copolymer material called ABS, and the temperature of the copolymer material is between -20 °C and 70 °C, as shown in[11], similarly, the temperature range supported by servo motors and other electronic components is similar to the above values. Robot has been used to store temperature values from -10 °C to 55 °C due to its difficulties in raising ambient temperature.

Due to a highly reliable electronic card, the performance of data storage and processing is better than other programmable devices. In this special case, the data obtained during scanning must be stored in Python. A function allows all data to be saved in a CVS file (comma separated values). They are text files, and their values are separated by separators. Generally speaking, the first line is the title which includes the name of each data column or field. Values are separated by commas[12].

3. Result

The system is developed with free and low-cost components and technologies to ensure that the developed technical applications can be maintained without increasing costs, and can be used by academia for further research. The ground tested on the hexagonal robot is 175

cm^2. The original model of the hexagonal robot[6] is slightly modified because it needs to use more robust processing to embed the Raspberry Pi 3 model B card into an adaptive platform.

3.1 Dynamic analysis of particulate filter

Through the particle filter algorithm, the actual path of the robot in the moving process can be determined. In this path, different landmarks or scattered reference points are placed in the whole environment, so that the robot can locate, provided that it is located in the designated area and can obtain the reference position related to landmarks. In **Figure 3** the view of the path set can be observed through random value deposition x, *y* (represented by continuous strokes) and particle adjustment. These particle adjustments create the path map of the robot from the initial preset path value of the robot, in which the motion error of the robot is regarded as represented by discontinuous strokes. The amount of noise introduced into the algorithm is of the same magnitude as the noise typically appears in experiments with real robots suggested in[3]. The figure compares the actual *x* position with the *x* position estimated by the particle filter to evaluate the quality of the results and determine the figure of *y* position (see **Figure 4**). It can be seen that although the average error level is calculated, the position estimation of the filter is quite prominent.

Through the calculation of particles, a necessary condition for determining the optimal design of filter is given, which ensures the estimation of sampling point position and greatly reduces the mean square error of equation (1); the error comparison diagram is made for each change of *m* value (particle number) shown in the **Figure 5**. In this figure, it can be clearly observed that the estimation error decreases with the increase of the number of particles used. It can be seen from the figure that the localization of 800 particles is enhanced, and it shows that good results can be obtained by using 1,000-1,500 particles.

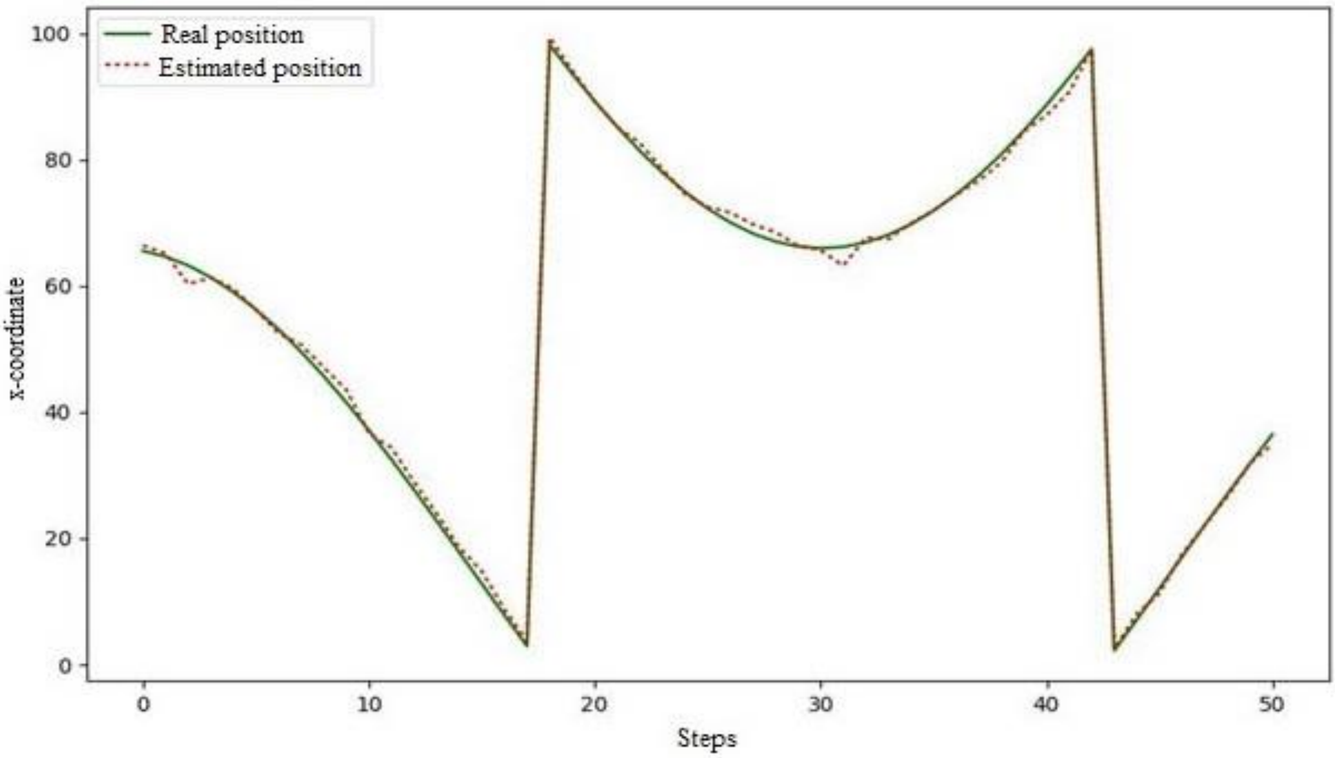

Figure 3. The actual *x* position of the robot *vs*. The position of *x* estimated by filter.

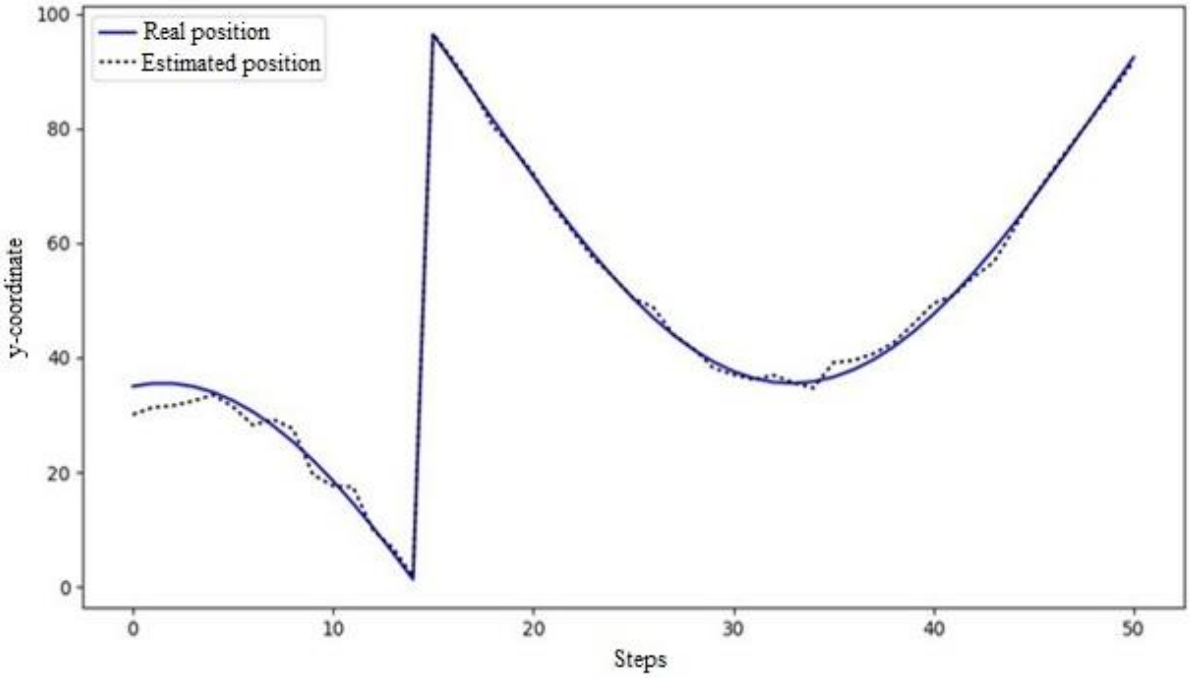

Figure 4. Actual *y* position of robot *vs*. The position of *y* estimated by filter.

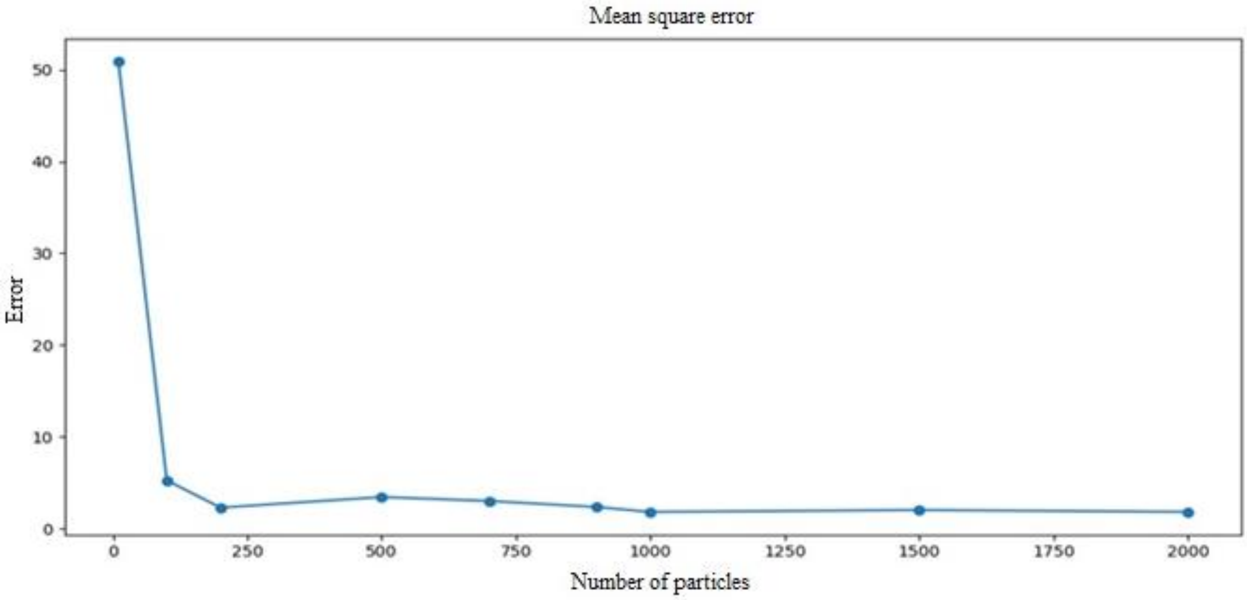

Figure 5. Comparison diagram of particle number error.

Due to the high computational cost of SLAM algorithm, it is necessary to calculate the processing time of Raspberry Pi 3 model B card to determine the time required for the system (**Table 1**) to estimate the position according to the number of particles set for its best performance.

Figure 6A and 6B show the robot in the test space. The robot perfectly recognizes the terrain by determining its position relative to the landmarks found in the environment. However, as long as the physical conditions of the scanning area remain unchanged, the position of each landmark in the algorithm is set to a constant data.

Table 1. Processing time of Raspberry Pi card

Number of particles	Processing time
10	0.1737992
100	1.2880270
200	4.1797537
500	6.0745110
700	8.4064073
900	11.2124450
1,000	11.5560207
1,500	19.7074775
2,000	28.3417411

Due to the limitation of the response time of the system (see **Table 1**) and the measurement noise of the sensor determining the position of the robot relative to the fixed reference system, the robot walking delay is mainly due to the calculation of new particles. Similarly, the results of implementing part filter in a small scanning area of a specific scene are also visualized and compared with the behavior in the simulation process. When the robot represented by the red circle is in the position corresponding to the landmark, the particle recombination shows a higher density, and the landmark shows a melon colored circle around the robot.

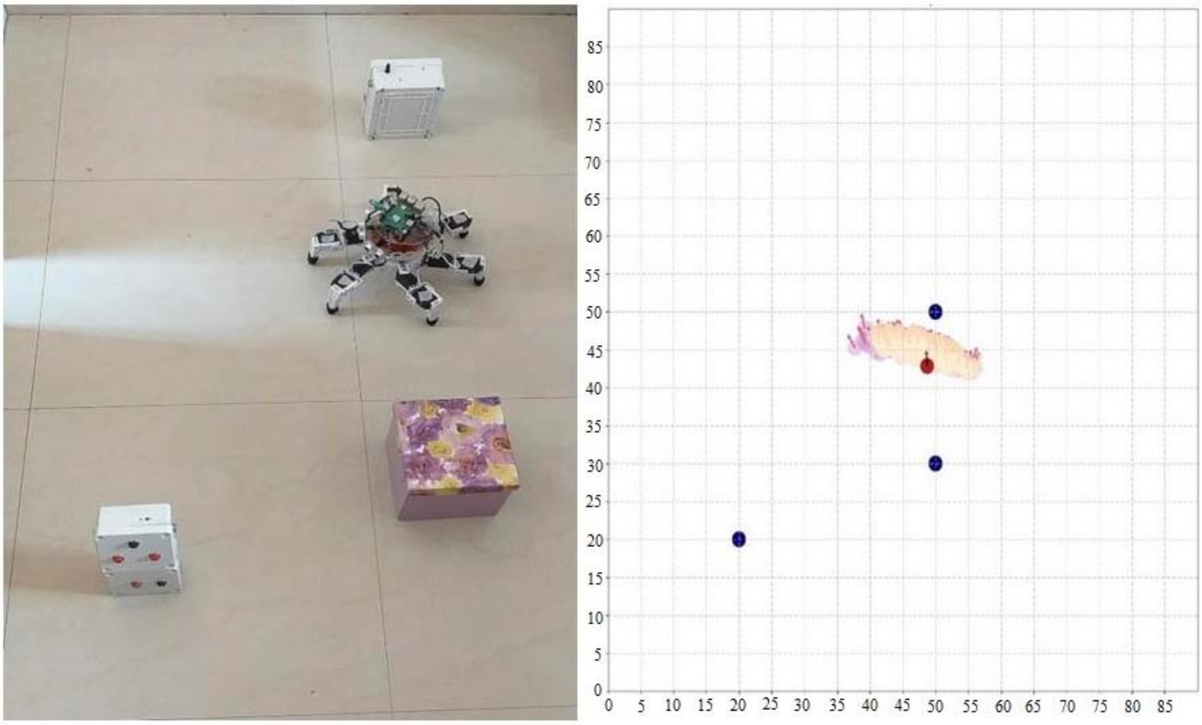

Figure 6A. The hexagonal robot updates its position relative to the landmark.

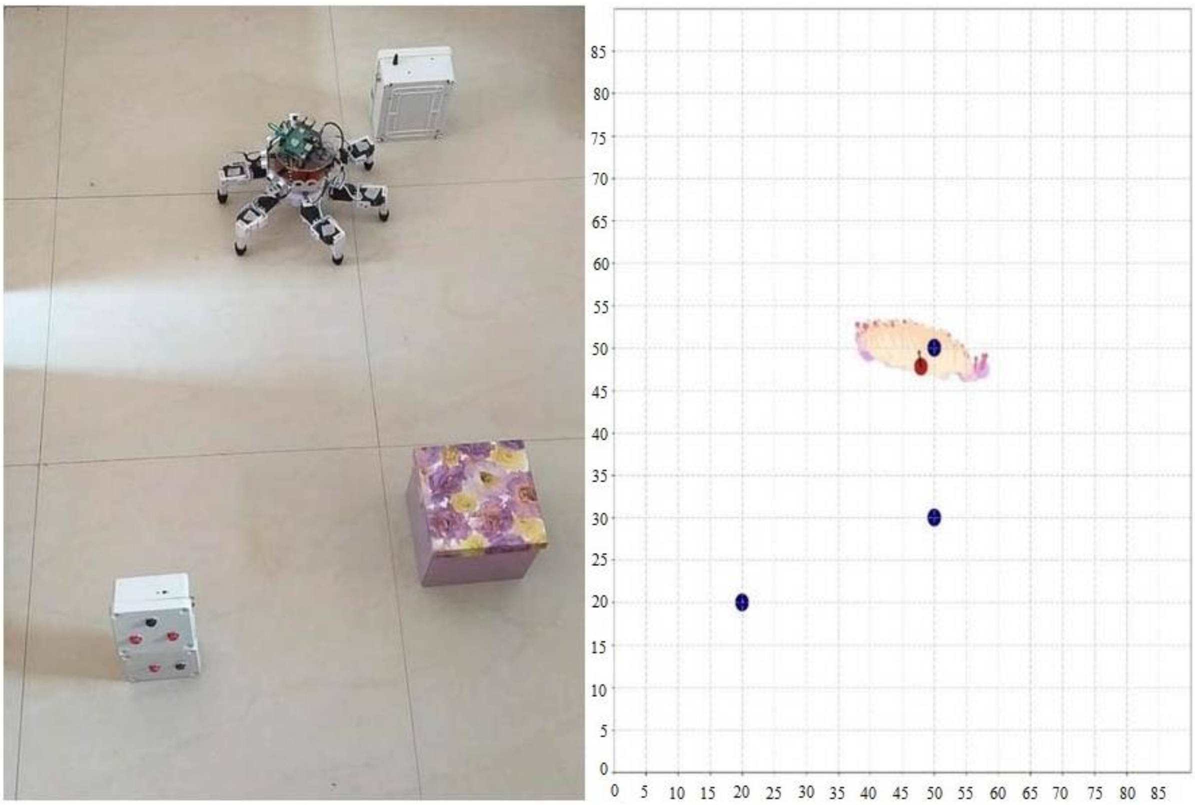

Figure 6B. The position of the hexagonal robot is updated relative to the landmark.

In order to update the position of the robot, the nature of the algorithm must be considered. Two iterations are needed to calculate the future position of the robot. Therefore, there is a certain error range between the actual position and the estimated position. Therefore, the more iterations or steps the robot gives, the greater the possibility of error in its current position.

3.2 Temperature analysis diagram

During the scanning process, through the DHT-11 sensor, the temperature data acquisition system is configured to automatically collect the value according to the input variables (position and temperature) every 35 seconds and save it in the CVS storage file. Through the sampling test using this sensor, it is found that the stabilization and acclimatization time to determine the correct temperature varies between 35 and 40 seconds.

When the robot completes its journey, it establishes a network connection with the computer and draws a temperature diagram according to the obtained data. The temperature value is represented by the color range, which changes according to its intensity, as shown in **Table 2**. These color ranges represent the range of colors defined at each point in the journey, as shown in the Figure. 7 and 8, these data are collected on the sensor 7 cm away from the heat source, and the ambient temperature is about 30 °C. The method used to determine the temperature region is to triangulate the surface and draw a triangle according to the temperature points within the same temperature range according to the color code specified above.

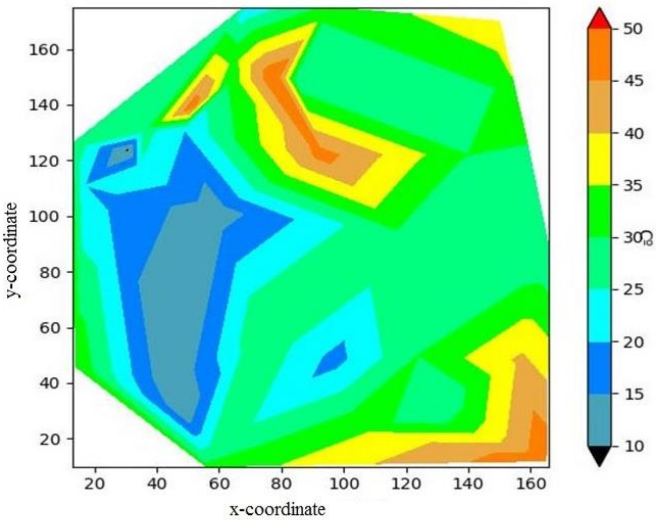

Figure 7. Temperature diagram.

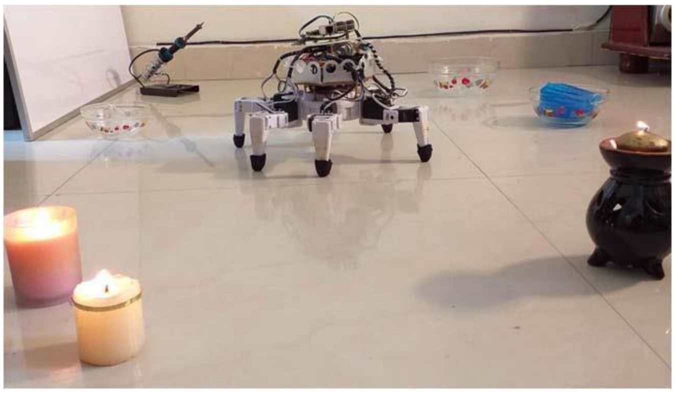

Figure 8. Temperature source in actual environment.

4. Discussion

Localization plays a very important role in the autonomous navigation of mobile robot. Therefore, to analyze several possible methods to solve this problem, it is necessary to study the application of the algorithm in robot system and the accuracy of the results.

Particle filter improves the position estimation of the robot relative to the fixed reference system, but the algorithm does not consider the discovery of objects or obstacles that may not only hinder the robot from moving in the scanning process, but also produce uncertainty for the change of gait direction that may lead to immediate position update. Due to the application of the algorithm in the field of autonomous navigation, the algorithm calculates various positions or steps of the robot moving and updating parts in the environment. In this case, the algorithm becomes a little rigid, and sudden changes are not allowed before all iterative calculations are completed.

Table 2. Color distribution according to temperature level

Colour	Temperature
Black	<10 °C
Celeste	10 °C < T < 15 °C
Blue	15 °C < T < 20 °C
Turquoise	20 °C < T < 25 °C
Emerald green	25 °C < T < 30 °C
Lemon green	30 °C < T < 35 °C
Yellow	35 °C < T < 40 °C
Mustard	40 °C < T < 45 °C
Orange	45 °C < T < 50°C
Red	>50 °C

Considering this function, particle filter cannot guarantee 100% successful positioning, because the rounding error is the inherent error of external sensors and gait fault-tolerant estimation of robot motion types. Therefore, in order to reduce the position error level of the robot, a position correction factor calculated from the above fault must be added to make the algorithm an advanced position monitor with continuous updating characteristics.

In order to monitor or sample the temperature, humidity and other climatic characteristics in the exploration area, it must be considered that in order to better study the variables affecting the sampling area, sensors with high average accuracy and data reading stability time less than 10 seconds are required. In this way, we can obtain better temperature RA diagram more accurately. For different applications, this represents a simple and fast method to detect any changes or abnormality in the analysis process. For safety reasons, when the robot detects the strength of the upper mark at a temperature of 55 °C or below 10 °C, it will change the driving direction within 25 cm from the ground mark.

5. Conclusion

The results show that the application of the system has achieved satisfactory results in using particle filter to determine the mapping and positioning (position) in the travel of hexagonal robot, the position estimation error level is less than 6%, and 1000 or more particles are applied to make the robot approach the location calculated by Algorithm.

Although the DHT-11 sensor can correctly collect temperature data and the measurement error is very low, it is inconvenient to obtain the stability time of new measurement and data acquisition failure usually occurs. Therefore, it is recommended to use another sensor to draw a more accurate map and use more sampling variables.

It is found that since there is no problem with signal interference, the wireless communication between robot and computer can be maintained, so the data collected by DHT-11 sensor can be displayed; Raspberry Pi3B card is used to correctly store the collected temperature data, and the temperature value of the whole lathe is well fitted. This determines that using the registry to generate CVS files is a necessary support for sampling without a network connection. The proposal solves the problem of energy saving and allows more scanning time. This network free environment is an ideal solution for applications under extreme conditions, such as lack of access to some areas that need scanning and data sampling, or including the development of low-cost rescue robot models to help the country in case of natural disasters.

Conflict of interest

The authors declare that they have no conflict of interest.

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Original Research Article

The Status Quo of José Ortega y Gasset's Supernatural Concepts: From the Perspective of Artificial Intelligence

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ABSTRACT

The first text of José Ortega y Gasset thinking about technology was published in 1935. Nearly a century later, this paper attempts to save a concept put forward by Spanish philosophers in *Meditación de la técnica*, that is: supernatural. Today, the biggest challenge facing technology is to maximize artificial intelligence and make it a means to challenge the restrictions imposed by nature. One of the most prominent suggestions in the field of artificial systems is superintelligence and uniqueness, which are the two most desired wishes of thinkers such as Nick Bostrom or Raymond Kurzweil. Therefore, if the field of technology is vigorously developing artificial intelligence, we should ask ourselves whether the motivation behind this momentum is really based on human needs for supernatural phenomena, which Ortega y Gasset have been talking about.

Keywords: *Artificial Intelligence; Vital Project; Singularity; Supernatural; Superintelligence*

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1. Introduction

Therefore, technology is a powerful response to the nature.
Source: Ortega y Gasset[1]

According to Diéguez[2], the reflection of the philosopher José Ortega y Gasset on the technique, and specifically on his work Meditación de la técnica[1], source of his philosophy of technology, has been scarcely treated, despite its avant-garde character. In 2000, Revista de Occidente and the Ortega-Maragnon Found organized an International Conference on Technology in Ortega, which showed their obvious interest in restoring Ortega's thought in order to explain it in the light of the current situation. Therefore, the main purpose of this work is to save one of the most important concepts, supernatural force, from Spanish mythology, so as to carry out contextual practice from the perspective of artificial intelligence. It is important to pick up baton from thinkers like Ortega who help to better understand the state of human technology and put it into practice from now on.

Ortguiano's narrative contains three anthropological characteristics that are essential to understand the technical aspects of human beings: ingenuity, constructiveness and natural advantage[3]. These anthropological features help humans upgrade their lives into a project and show their desire for happiness in the world. This happiness is infinitely changing and can meet the needs of the moment. The technology here is understood as a proactive response, which can defy nature and overcome the limitations of nature on human beings.

At present, supernatural phenomena are hidden in the creative dream of artificial systems, which can surpass the ability to control human intelligence. In this regard, the concept of Ortguiano supernature, which will be elaborated in the first part of the work, is linked to two assumptions in the field of artificial intelligence-superintelligence and uniqueness. The method of this connection is to observe Ortega's thought from the current perspective and emphasize the importance of artificial intelligence to life. Artificial intelligence is understood as a technical project and part of the historical and technical conditions of human beings in their efforts to respond effectively to the restrictions imposed by nature.

Mitcham[4] acknowledged that José Ortega y Gasset was the first to deal with technical problems. The most important work of Spanish philosopher where the subject of technique is addressed is *Meditación de la técnica*[1]. In the preface, Ortega pointed out that the work originated from a summer course offered by Santander university in 1933. However, after the course, the lectures were fragmentedly published on Sunday articles in the newspaper *LaNación* of Buenos Aires in 1935. Finally, in 1939, *Meditación de la técnica* were published together with another article: "Self-awareness and change." There is also another important text that collects the lecture *The Myth of man beyond technique*[5], published by Ortega in the German city of Darmstadt in 1951. As Esquiol[6] pointed out, Ortega's reflection on technology is "inserted in the nucleus of his philosophy of life and his understanding of the human condition" (p. 15). There is a very important work in Ortega's ideological history, prior to his *Meditación de la técnica*, and which will mark a before and after in his work, *The Revolt of the Masses*, 1929. In this work, technology is regarded as the creator of the human masses. Although the treatments that technology receives in the last two works mentioned are different, they are consistent in providing basic guidance to understand the impact that technology has on human beings and their lives. Technology is in the relationship with existence, starting from three key concepts: necessity, estrangement and project.

Humans live in the environment and are surrounded by nature. Nature gives humans some needs that must be met, such as protection from the cold and food. Life is connected with needs, and humans strives to meet these needs because they want to live. In this regard, a series of activities have been launched to meet these needs, thus creating the necessary conditions for meeting these needs, such as planting systems, shelters that can withstand the cold, etc. As the philosopher himself pointed out, these activities mean that the most basic needs can be put aside, "Thus, heating, farming and the manufacture of wheelbarrows or cars are not our actions to meet our needs, but rather, on the contrary, they mean the opposite: to stop the original behavior of our direct pursuit of satisfaction"[1].

Ortega first considered the necessity in his works:

Therefore, technology is a strong response to nature or the environment, which leads to a new nature and a supernatural phenomenon between man and nature. Therefore, please note: technology is not what human beings do to meet their own needs [...]. Technology is the transformation of nature, which makes us needy and needy. This transformation means that if possible, these needs will be annulled because meeting them is no longer a problem[1].

Human beings do not adapt to the coming environment, so their response to these environments is good, so he will not listen to fate, because it is not just about "being", but about "being well". Therefore, he skillfully created the supernatural forces on which Spain's philosopher relied. But the real commitment is to being well in this world, so it does its best to ensure this well-being. Therefore, what is objectively superfluous becomes what is regarded as the only necessary[1]. Ortega's view on biological needs, objectively speaking, is not human needs, but when they are regarded as the conditions in the world of subjective needs in this sense, they become real needs. Ortega believes that they are subjective, because the existence in this world is something that guarantees future happiness and is accepted as super happiness.

Recalling the concept of "estrangement" mentioned earlier, it must be pointed out that man has created a world different from the world previously given to him, because he feels that he does not belong to this world; He felt strange and uncomfortable. Mankind is facing a world that brings him an environment that he does not agree with, a world that is strange to him; therefore, he had a will, a determination to establish a new world, a new nature and a supernatural phenomenon, in which he was found to be excluded and excluded. The given world is strange, which is why it is another world created by a supernatural technology and impulse. Esquirol[6] made an important contribution when pointing out that estrangement ideas are similar to Heidegger's "abandoned"[24].

The concept of need is linked to the concept of well-being, but it is difficult to determine what well-being is because there seems to be no agreement on well-being and technology. Happiness is related to time, space and culture; Therefore, it changes with the passage of time and people's differences, which is why the concept of defining it becomes complex. Therefore, the concept of happiness is variable because it is associated with a concept of how life is understood. This means that according to the life project you decide to pursue, the idea of what happiness is must adapt to demands and needs.

However, it must also be pointed out that changes in the nature of well-being are accompanied by changes in technology, and here is where Ortega's[1] words need to be saved:

We just need to fundamentally change the happiness shrouded in human beings and experience a certain degree of change in the concept of life. From this, what is all human beings do for? In this way, the traditional technology will collapse, collapse and fall into another dilemma. (p. 32)

In this regard, as pointed out by the Spanish philosopher, technology is also changing because it depends on the concept of well-being.

This technology creates a vacuum as it tries to save effort. For example, think about today's world, where there are technical devices for releasing tasks, such as smart slippers, garden sensors, smart garage doors, dog clothes, dimmers, smart dustbins, etc. They want to meet their needs with minimal effort and keep good. In short, technical behavior is not an effort to directly meet objective or subjective needs, but an action to respond to situations requiring efforts, first to invent and then implement previously proposed plans or projects. According to Ortega[1], the plan or project referred to shall allow: (1). Ensure that basic needs are met. (2). Achieve this satisfaction with minimal effort. (3) Create our new possibilities by making things that are not in human nature. Therefore, sail, fly, talk to each other by telegraph or radio communication.

Human beings have successfully confronted the environment and defied them through the reforms provided by technology, thus reducing the efforts brought by this environment, which is dominant in creating supernatural forces. In addition, in this kind of technical action characterized by saving efforts, there is also the pursuit of security, because the environment leads to an uncertain and unsafe space that hinders complete development and causes estrangement.

Ortega[1] warned that progressivism based on blind and undeniable belief in technology led to cultural decline. Lack of flexibility can lead to human confusion, because supernatural phenomena are the same as nature and completely lose awareness of the technology used. The continuous predominance of technology in life have generated a difficulty when it comes to live materially without it.

2. Life as a project

The concepts of necessity and estrangement have been addressed in order to clearly approach Ortega's ideas on technology, but there is still a need to redefine the project concept, which is linked to his proposals on life and historical causes. The labor saving brought by this technology creates the possibility of using time and imagining projects. With the liberation of technology from efforts, what is spare time used for? According to the Spanish philosopher", this is where human beings must invent their own life and create their own life, as if he were "the craftsman of their own life", which is used by Cortina[7]. In this way, man must create his own life story, and he must project himself. In this sense, this technology will be associated with the concept of human meaning, because it will have the nature of Anthropology and ontology. Ortega's philosophy of technology is based on his concept of human life, which is understood as a phenomenon that shapes its significance in the active relationship with the environment, that is, as the active creator of these environments. It is a life project, which shapes its own existential rationality in the interaction between man and environment.

Human life is not something given by nature, something that is completely determined by nature; therefore, it is not given by existence. Instead, one must create oneself by designing a life project. Human beings slide their existence from an activity of self-interpretation and self-creation, emphasizing themselves, but also emphasizing the environment that urges him to respond through projection. In this positive existence, there is a creative imagination that provides its own strength to the personal projects it wants to achieve. Once human beings decide what projects to assume and undertake, they need material and technological resources to complete such a project. In this sense, for Ortega, this technology means the opening of a new possibility, which aims to create life, to create that life in which human writes his own story because he is a project, whether he is a gentleman, Bodhisattva or Hidalgo. Human life is not defined by nature. It is destined to be an upcoming project and the product of their creative imagination.

From those suggestions on human self-realization, Ortega's ideological line can be regarded as a Faber, not a Faber limited to material production, but a Faber responsible for self-projection and writing the story of his own existence. Spanish philosopher is implementing a technical scheme to understand people as a project and emphasize the architectural concept; for this reason, it uses the word "self-made" and "therefore, our life is a pure task and an unstoppable task"[1].

Ortega's understanding of life is based on his understanding of rationality. Rationality is deeply related to life experience, because it is nourished from life. His view of life was elaborated in his speech at the 1906 Valladolid Floral Games, in which he understood life as "more life" as self-improvement or "henchmento", as Conill[8] said. Ortega's outlook on life was inspired by Nietzsche's thought. In this sense, just as life is an adaptation to the environment, it is also the creation, courage and will of life.

As mentioned above, Ortega's understanding of life is developed from his new philosophy of life rationality, which reflects all aspects of Nietzsche's thought to a certain extent. In addition, Ortega's contribution mainly focuses on his reflection on the desire crisis and the necessity he put forward in cultivating and shaping life projects, because technological desire marginalizes human's real desire, that is, the desire for self, and shifts the attention to personal projects. Therefore, the Ortega desire crisis emphasizes that superfluous desire feeds the inner emptiness. Humans find themselves bewildered and saturated in the face of so much technology, and in a sense feeds his artificial desires. However, he was disturbed by the awareness of his main limitation, that is, the limitation in the face of the excess of possibilities inherent in technology.

3. Artificial intelligence and its current situation

Since the object of reflection of these pages is oriented to the reflection on the current supernatural concept of Ortega from artificial intelligence, it is important to briefly introduce this amazing new technology artillery. First of all, efforts must be made to define the concept and significance of artificial intelligence in order to promote the understanding of the phenomenon of artificial intelligence.

As has happened in many areas of conceptualization, there are many definitions around AI, each from a different perspective, although they all seem to have one thing in common. This common ground is a basic idea, and various suggestions revolve around the idea of creating and shaping computer programs or machines that can develop a behavior that, if implemented by humans, will be considered intelligent. This definition is open ended and consensus can be reached, because various definitions provided by some field experts are often closed and different from each other. Therefore, at least in this case, it is best not to close it. This method based on human brain simulation is similar to the proposal made by John Mccarthy, Marvin L. Minsky, Nathaniel Rochester and Claude Shannon in 1955[9]. In addition, with regard to the definition of AI, the British Boden[10] also pointed out the following:

The purpose of artificial intelligence (AI) is to let computers do the same things as the brain.

Some (such as reasoning) are often described as "intelligent". Others (such as vision) are not. But they all involve psychological abilities (such as perception, association, prediction, planning, motion control) that enable humans and other animals to achieve their goals.

Intelligence is not a single dimension, but a structured space composed of various information processing capabilities. Similarly, AI uses many different technologies to solve a variety of tasks. [...] Artificial intelligence has two main goals. One is technological: using computers to do useful things (sometimes using methods very different from those of the brain). The other is science: using artificial intelligence concepts and models to help solve human and other biological problems[10].

The above paragraph does not exclude the possibility of reaching a consensus on certain intellectual markers in many specific texts. Doubt arises when you try to apply these markers to the machine. For example, if we consider the arduous task of ancient Egyptian scribes in copying texts and imparting knowledge, and compare it with today's textbook printing press, the machine will be "smarter" because it copies texts faster than humans; in this case, the speed marker has been taken into account. As you can see, marker speed is not an effective indicator to consider a machine smarter than humans.

It may be a problem to regard human ability as an effective standard for evaluating artificial intelligence. A machine can complete a task in milliseconds, while a person cannot complete similar tasks in a short time; this is why we might think that this machine seems to show wisdom. Such events will occur in hundreds of fields in the coming decades, and in many fields they have already occurred. Therefore, using the comparison method between human intelligence and artificial intelligence may lead to absurdity, because human intelligence is always lost in all cases. This shows once again that it is not easy to try to provide a specific AI definition.

In recent years, people have been talking about the fourth industrial revolution. For example, in one of his works, Schwab[11] focuses on analyzing how artificial intelligence plays an important role in the new technological revolution that changes mankind through the integration of digital, physical and biological systems. Since artificial intelligence, the most advanced new technologies are promoting great changes in the way people establish relationships with the world, work and life organizations. Rouhiainen[12] believes that AI is the most important element in the fourth revolution because it represents an important hinge and bonding axis of other components (p. 38). The challenge of the fourth industrial revolution lies in knowing how to deal with a series of changes resulting from exponential growth for which citizens are not prepared. In today's artificial intelligence, human beings are facing double challenges, that is, how to correctly understand and use these technologies.

After exposing some main characteristics of artificial intelligence and its current applications, it is important to summarize some of the most prominent suggestions on the future and development of synthetic intelligence in recent years. These suggestions can focus on the renewal of Ortega y Gasset's concept of supernatural force: superintelligence and uniqueness.

4 Superintelligence and uniqueness

Bostrom[13] defined superintelligence as "any intellect that significantly exceeds human cognitive ability in almost all areas of interest" (p. 22). Swedish philosopher is a firm supporter of the cross humanistic movement, therefore puts forward the idea that it is easier to develop intelligence on an artificial basis than on a biological basis, because machines have many advantages that biological entities do not have.

The idea of surpassing human standards is not new. For example, cats have a much more sensitive sense of smell than humans, and calculators do math exercises much faster than math teachers. However, when we talk about artificial intelligence, it is the basis of a series of additional entities whose intelligence is so large that they can replace human beings in any field. Therefore, Bostrom[13] proposed the following classification to distinguish superintelligence: speed superintelligence, collective superintelligence and quality superintelligence.

Bostrom[13] believes that any of these three types of super intelligence may develop other types of super intelligence. In this regard, it can be assumed that there is a reason for this, and once artificial intelligence reaches the level of human intelligence, there is likely to be a superintelligence explosion, which means that synthetic intelligence is independent outside the programmer and can form and shape other intelligence. Therefore, the phenomenon of superintelligence has triggered a profound ethical reflection, because we are not talking about a folk theme, but a theme committed to humanity in an important way.

Bostrom's[13] so-called "kinetics" of an intelligent explosion shows how synchronization and take-off speed could occur when artificial intelligence reaches the level of human cognition. When AI reaches the same cognitive level as human beings, different paths can be seen on the horizon. However, considering the requirements put forward in this article by Bostrom[13], it is important to consider the transition phenomenon, because there is a high probability of the so-called superintelligence explosion. Although this is part of a predictive study, the importance of the study conducted by Müller and Bostrom[14] should not be underestimated.

Table 1 shows the results of four different surveys and their combinations. Survey participants are presented in the documents of Müller and Bostrom[14]. Despite the predictability of the survey, Bostrom almost believes that superintelligence is possible soon after artificial intelligence reaches human level. Bostrom[13] is not the only one who supports this idea, as there are other recognized figures, such as Barrat[15] or Tegmark[16], followed.

Singularity is another term used in the field of artificial intelligence, which refers to super intelligent system. It can improve itself and create other systems, even smarter than itself, following exponential growth. Here we can simply mention the kinetics problem or singularity of super intelligent explosion, because it is closely related to the growth rate. The advocates of the singularity believe that when in the future the best developers are not flesh-and-blood people, but artificial intelligence itself, the performance of artificial intelligence, which initially attributed to hardware, and later through revisionism, to software, will be greatly doubled, and the speed of artificial intelligence will be the usual norm. Therefore, if the self-designed speed of artificial intelligence is infinite in the future, higher-level intelligence is very likely and almost self-evident, which may make people think that the explosion of superintelligence is possible.

The biggest representative of singularity is American Raymond Kurzweil[17]. He believes that singularity can be self-improvement, taking the composition of the whole universe based on an intelligent global entity as the horizon. Americans believe that when a synthetic intelligence exceeds human intelligence, progress will be much faster. Kurzweil[17] and Moravec[18] believe that machines will surpass human intelligence in the first half of the 21st century. According to the AI expert, the growth of AI will be exponential:

It represents an almost vertical phase of exponential growth. When the speed is very high, technology seems to expand at a very fast speed. Although from a mathematical point of view, there is no interruption or rupture, the growth rate remains low, albeit very large. However, from our current limited framework, this imminent event seems to be a sharp and sudden breakthrough in the continuity of the progress[17].

As Kurzweil's book[17] said, the singularity is at hand, which will mean a paradigm shift in several areas mentioned by the American expert in his book. By the end of this century, most intelligence is expected to be nonbiological; however, this does not mean the finish of biological intelligence. Kurzweil[17] is a firm defender of singularity+. In this regard, he is very optimistic because he believes that superhuman intelligence will meet our needs and desires. His suggestion to avoid the ineffectiveness of humans, because humans are likely to be manipulated by machines, or as Carl[19] said, "trapped", is the integration with machines, although he calls this "intimate connection"[17].

Bostrom[13] and Kurzweil[17] have a lot in common: the former speaks of superintelligence and the latter speaks of singularity. Both thinkers believe that artificial superintelligence will dominate many human fields in this century unless they take the measures they propose. Therefore, for Kurzweil[17], it is recommended to closely integrate with machines, and for Bostrom[13], it is recommended to insert ethical behaviors with axiological content.

Table 1. AI experts' findings on when human intelligence appears

When will we get the level of artificial intelligence?			
	10%	50%	90%
Pt-ai	2023	2048	2080
Aji	2022	2040	2065
Eetn	2020	2050	2093
Top 100	2024	2050	2070
Combined	2022	2040	2075

Source: Adapted from Bostrom[13].

Synthetic intellects as a means of overcoming limits.

For Ortega y Gasset[1], technique represents a conditional means by which human beings shape and control themselves so that they can break the restrictions imposed by nature. The technical conditions that the Spanish philosopher confirms to the humans can establish a close link, by way of clarification, with the concept of "homo Faber" proposed by Arendt[20]. It is well known the distinction that Arendt[20] establishes in *The Human Condition* between labor, work and action, as those activities in which the human beings has deployed his life: .labor, related to human biological processes, having life itself as a condition; work, related to the production of handmade objects; and action, which is the activity of human beings without the intermediary of things, having plurality as the condition. Although labor and work are carried out in the private sphere, action belongs to the public sphere. Arendt[20] distinguishes work from labor, taking into account the difference that Locke[21] establishes between both concepts: "The labor of our bodies and the labor of our hands" (p. 226). The author points out that:

Labor is an activity corresponding to the biological process of human body. Its spontaneous growth, metabolism and decline are related to the life needs generated and nourished by labor in the process of life. The human condition of labor is life iteself. Labor is an activity corresponding to the unnatural needs of human beings. It is neither immersed in the repeated life cycle of species, nor dies due to this cycle. This work provides an "artificial" world that is significantly different from all of the natural environments. Within its boundaries, every individual's life is sheltered, while the world survives and transcends all life. Human working conditions are secular[20]. Through this work, Arendt[20] pointed out that human products reflect their culture and have a certain durability. Therefore, it distinguishes between working animals committed to survival and Farber people who create a world in which human beings live together. Human factories develop their production by evaluating, selecting and using appropriate means to achieve certain goals. In addition, the relationship between Faber people and media is the possession and utilization of nature; therefore, it has the ability to create and destroy its own consumer goods.

For the Orteguian anthropology, man is a project in himself, who focuses on writing his own life story. In this sense, artificial intelligence is a technical means, which can eliminate the restrictions of nature on human beings, so as to realize the projection of dreams. Artificial intelligence is a technical mechanism to challenge the limitations of nature. It is to build the ability on the machine to do things that human beings cannot do due to the limitations of nature. Men project what he cannot become into synthetic intelligence and artificially creates the ability to surpass nature and enter the supernatural. The construction of this artificial ability is because it imposes a human welfare model, which is ever-changing. It is the power of creation that grants him the possibility of walking into to the infinite supernature.

Artificial intelligence is the highest expression of human spirit. This spirit is the variability that constantly challenges the limits of nature. This is the result of an Android dream that began with Alan Turing[22] and Toby Walsh[23]. Although people sometimes have doubts and fears about artificial intelligence, this is a major trend of our times. The purpose of synthetic intelligence is to let computers do what human beings can do through the intelligent ability generated by the brain system; they put themselves on the horizon of possibility, which is only the theme of science stories so far. Artificial intelligence can imagine many aspects of reality that human brain cannot imagine because of its natural cognitive limitations. In addition, it can transcend the biological boundary of memory, accumulate more information than the human brain, and process more data at a speed that human beings cannot imagine. These are examples that go beyond the above limitations imposed by nature on human beings and the methods to eliminate these limitations through technology. In this case, artificial intelligence is the representative.

5. Conclusion

Strengthening closer contact with human technology is crucial to gaining more anthropological knowledge. Concepts like the supernatural have positive contribution for human to cultivate understanding of humans and their limitations. Therefore, the reflection of technical conditions by Ortega y Gasset[1] provides quite rich content for this task.

As we can see, this Spanish philosopher's hypothesis is of great significance because it clearly recognizes the technical dimension of human existence. This existence is understood as a project, which is closely related to the technical conditions. This means that life is understood as a project, starting from the possibilities provided by technology. In this regard, the direction of action is to overcome the restrictions imposed by nature as part of the decided project.

The various manifestations of artificial intelligence (species-improving technology, nano-robots, autonomous vehicles drones, etc.) clearly show that people have been eager to go beyond the limitations of nature on its various manifestations. This advanced technology has opened up a series of unprecedented possibilities for mankind. This openness requires more understanding of mankind. The question about the hidden supernatural phenomena in artificial intelligence is also a question about who human beings are and the ongoing project. In addition, it helps to have a deeper understanding of the meaning reflected in the existential narrative, and also helps to provide broader understanding of restrictions. Supernatural phenomena are the result of good wishes for the world, which requires thinking about what kind of happiness concept promotes the design of today's technology.

Conflict of interest

The authors declare that they have no conflict of interest.

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Original Research Article

Data Analytics to Increase Performance in the Human Resources Area

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ABSTRACT

In a digital era, traditional areas like Human Resources have to adapt themselves to stay alive and competitive. The processes have been drastically changing from paper and talks into systems and workflows. Data is now more than ever in the spotlight and have become an essential asset to ensure delivery, performance, quality and predictability. But first, data has to be organized, combined, verified, treated and transformed to become meaningful information, not forgetting automatized to be delivered in time and supporting decision making in a daily basis. Business Intelligence (BI) is the tool capable to do it and we are the minds to pull it off.

Keywords: *Data; Analytics; Digital; Human Resources; Performance; BI; Power BI*

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1. Measuring the HR

One of the most crucial element of any BI model and Data Analytics is a well stablished data acquisition method, as Peter Drucker once said “You can’t manage what you can’t measure.”, but is it really possible to measure HR work? And what gains can we have? Digital tools and standardized processes are the key to allow it and if Peter Drucker (again) wasn’t wrong “What’s measured improves”.

For today’s standard remain competitive, very often it means to be cost-efficient while ensuring good services quality. In order to accomplish it and stay in front of the competition, data analytics prove to be a strong ally. Isn’t a simple task, HR is a very traditional area and to introduce a data-driven mindset can be challenging and probably only visible results can open the way for the digital transformation.

1.1 Data acquisition, definitions and reporting

Data can be anywhere at any format and it requires the right tools and skills to identify and mining it. In this work we faced the likes of nine different HR systems each one of them with their own purpose and format. Microsoft’s software Power BI was used to pull the data from all of those and make sense of it.

The ETL (Extract, transform and load) is handled by Power Query within Power BI, which has multiple connectors to bring data from a variety of sources and uses the M language to transform, merge, combine and enrich. It has to be done very carefully and takes in overall a considerable time to ensure data quality and accuracy for the next stages of creating reports, dashboards and KPIs.

Once ETL is completed, the data is transferred to a new environment inside the software, previously called as Power View, where you can visualize the treated information and build reports using a set of visuals (charts, tables, cards etc.) to help you to tell the story and bring the insights, also allowing you to take full advantage of the powerful DAX language to do from the simpler to the most complex calculations, called as measures within the software.

2. KPI and BI Dashboard

The KPI (Key point indicator) is a quantifiable measure used to evaluate the success of an organization, employee, etc. in meeting objectives for performance[1]. That said, it's required to be well defined by the leadership what are the measurable of the processes related to quality, performance and/or others factors that will be evaluated over time.

A business intelligence dashboard (see **Figure 1**) is an information management tool that is used to track KPIs, metrics, and other key data points relevant to a business, department, or specific process. Through the use of data visualizations, dashboards simplify complex data sets to provide users with at a glance awareness of current performance[2].

Figure 1. A sample of BI dashboard utilized by HR to follow up on KPIs, performance and quality metrics.

In a modern HR there will be traditional metrics related to the business like turnover, overtime and absenteeism, but also more recent ones related to the performance of the HR operating model such as SLA, backlog, response time and customer satisfaction survey.

3. SLA

A service-level agreement (SLA) is a commitment between a service provider and a client. Particular aspects of the service-quality, availability, responsibilities-are agreed between the service provider and the service user[3]. It's on the highest level of importance and directly reflects if the services are reliable and respectful with the customer expectations. The equation (1) show how it was calculated and the results (see **Figure 2**) can be analyzed over time before and after the implementation of data analytics.

$$= CALCULATE(DIVIDE([.Closed\ InTime];[.Closed\ cases]);\ [SLA\_time]>0) \quad (1)$$

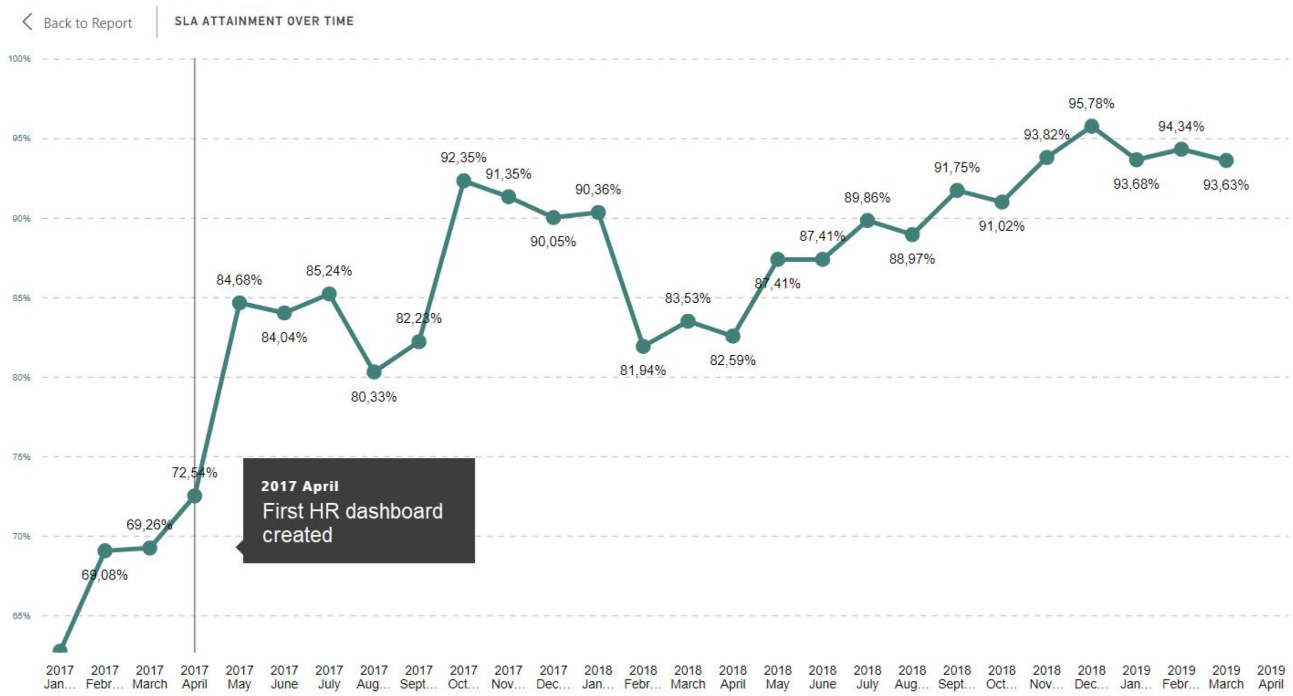

Figure 2. The SLA attainment over time of the HR requests, extracted from the HR performance report.

4. Backlog

Value of unfulfilled orders, or the number of unprocessed jobs, on a given day. Backlog indicates the workload that is beyond the production capacity of a department[4]. It can reflect how much stable or not the process behaviors and how sustainable it is over time, also has an indirect impact in the SLA and customer satisfaction. The equation (2) show how it was calculated and the results (see **Figure 3**) can be analyzed over time before and after the implementation of data analytics.

[.Opened (acum)]-[.Closed (acum)] (2)

[.Opened (acum)] = CALCULATE([.Opened cases] ;

FILTER(ALL('Calendar') ; 'Calendar'[Date] <= MAX('Calendar'[Date]))) (3)

[.Closed (acum)] = CALCULATE([.Closed cases] ;

FILTER(ALL('Calendar') ; 'Calendar'[Date] <= MAX('Calendar'[Date])) ; (4)

USERELATIONSHIP('Calendar'[Date] ; 'System'[closed date]))

Figure 3. The backlog of requests that HR had day-by-day, extracted from the HR performance report.

5. Response time

Customer response time is the period between the placement of an order and the delivery goods or services. It can also refer to the delay in communication or response from business to customer. In other words, it is the time between when a customer makes an inquiry about a product or commits to a purchase a good or service and when it is actually received by said customer[5]. Directly impact the customer and his perception of the services delivered. The equation (5) show how it was calculated and the results (see **Figure 4**) can be analyzed over time before and after the implementation of data analytics.

$$= IF([closed]="0";DATEDIFF([createdate];TODAY();DAY);[time\_to\_close]) \quad (5)$$

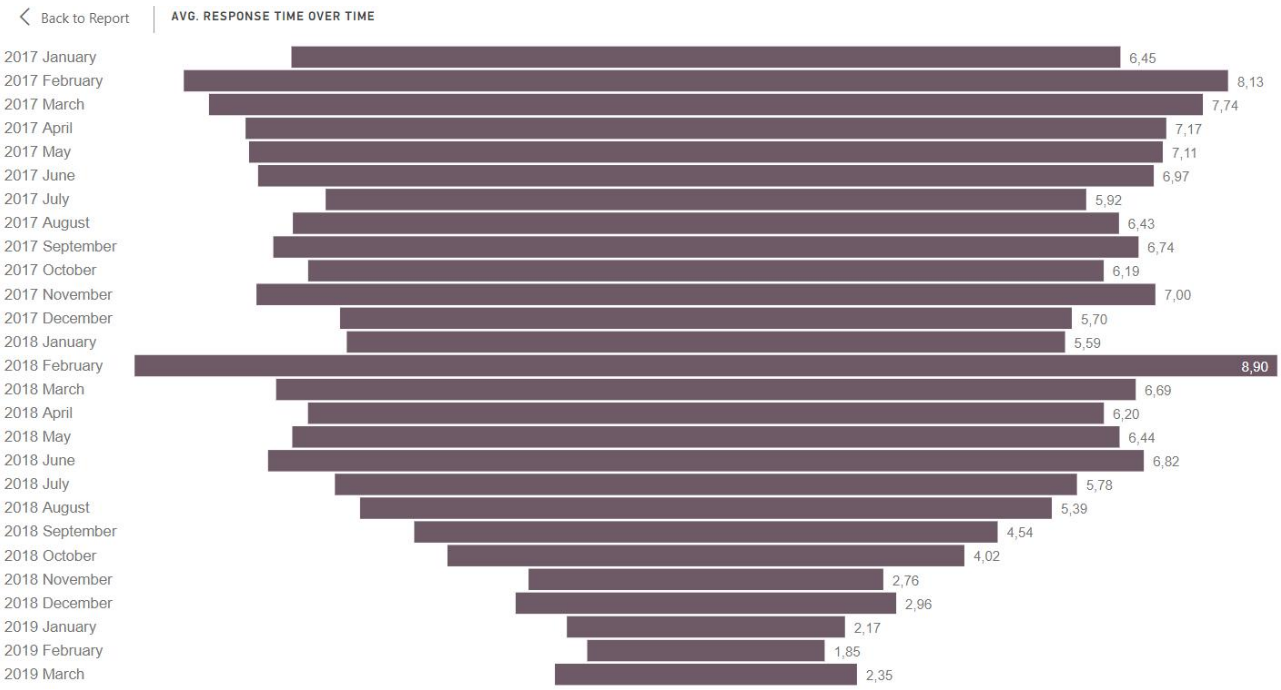

Figure 4. The average of the response time in days by month and over time, extracted from the HR performance report.

6. Customer Satisfaction Survey

Process of discovering whether or not a company's customers are happy or satisfied with the products or services received from the company. Customer answers to questions are then used to analyze whether or not changes need to be made in business operations to increase overall satisfaction of customers[6]. An important factor to ensure that services are being delivered not just within the agreed time but also with satisfactory quality. Results (see **Figure 5**) can be analyzed over time since it was implemented.

Figure 5. The overall result and the average over time of the customer satisfaction survey, extracted from the HR performance report.

6.1 Notes on the KPI and rates calculation

There is no universal convention on how to calculate those metrics and it can have different formulas for different companies and/or countries, depending on factors as such systems, culture, company values, labor law etc.

7. Final conclusions

Finally, we can attest that Drucker was right. Of course the amazing results we saw are merits of a lot of hard work from all HR people involved but is unquestionable that when you know and have property, ownership on something you can work to improve it more and more. The gains in performance were incredible in a relatively short period of time and with no increase of personnel, sustainable quality and predictability were achieved allowing the right allocation of resources in the right moment with data-driven decisions. Data analytics and BI tools has proven indeed to be a strong ally and partner to business even on traditional areas such as Human Resources, once you have the information operating without it is like operating blindly, there is no turn back, the hunger for information only increases. "In God we trust, all others must bring data." said W. Edwards Deming.

Data has already become a valuable asset for all type of business and the good news is it's getting bigger. According to Forbes, the amount of data we produce every day is truly mind-boggling. There are 2.5 quintillion bytes of data created each day at our current pace, but that pace is only accelerating with the growth of the Internet of Things (IoT). Over the last two years alone 90 percent of the data in the world was generated[7].

The rest of this paper is arranged as follows: Section 2 introduces related works including signal acquisition, signal preprocessing and feature extraction. Section 3 introduces the design method of deep neural network. Section 4 the experimental results are discussed.

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