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Track Circuit Fault Diagnosis Method Based on Support Vector Machine Algorithm

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Abstract: Rail transit is an important mode of transportation in urban construction. In recent years, China has put forward higher requirements for subway, light rail and other public transport tools. In order to improve the stability of rail transit, the support vector machine algorithm is used to improve the fault diagnosis ability to facilitate people. This paper mainly uses experimental method and comparison method to support vector machine, GA algorithm and other algorithms in track road diagnosis. The experimental results show that the recognition rate of some faults can reach 100%, which shows that the design scheme in this paper has some reference significance.

1. Introduction

Track circuit is an important part of urban rail transit, and its safety requirements are increasing. The subway is widely used as a high investment, large investment and long life cycle transportation mode. It accounts for a large proportion in China's railway construction. Traditional track circuit maintenance methods generally rely on manual maintenance and repair work to complete. In order to reduce labor consumption and control costs, this paper proposes the use of modern technology for fault detection.

There are many theoretical achievements in support vector machine algorithm and rail road fault diagnosis. For example, some scholars said that introducing incremental learning into support vector machine integration can make full use of the support vector set obtained from historical training results [1-2]. Some scholars also believe that it is of great significance to improve the intelligent level of railway signal maintenance by using genetic algorithm and particle swarm optimization algorithm to optimize the parameters and then realize the judgment of fault types [3-4]. In addition, some scholars said that support vector machines based on statistical learning theory showed excellent classification performance and became one of the research focuses in the field of fault diagnosis [5-6]. Therefore, it is of practical significance and theoretical basis to use the relevant algorithm of support vector machine for the research of rail roads in this paper.

In this paper, support vector machine (SVM) is studied firstly, and its application in fault diagnosis is introduced briefly. Secondly, the fault diagnosis design scheme of track circuit is analyzed and discussed. Then the track circuit fault comprehensive diagnosis based on SA algorithm is described. At last, the related algorithms and the ability of fault diagnosis are tested through experiments, and the final conclusions are drawn.

2. Track Circuit Fault Diagnosis Based on Support Vector Machine Algorithm

2.1. Support Vector Machines

SVM is a two classifier, and with the requirement of maximum distance, it can be transformed into a convex quadratic programming problem by introducing corresponding conditions. Advantages: The advantage of SVM theory is that it uses corresponding forms to replace the complex operations in high-dimensional space, thus preventing the so-called "dimension accumulation" problem in high-dimensional space. Its kernel function is a continuous symmetric function in the real number field. Generally, functions conforming to Mercer's principle can be regarded as kernel functions. SVM algorithm mainly focuses on small samples, and is difficult to implement for large samples. SVM relies on the QP problem to find support vectors, while solving the QP problem will involve order x real/complex sets, and x is in direct proportion to the training complexity [7-8].

Based on the analysis of support vector machine, a new method of track circuit fault diagnosis is proposed, which combines the improved statistical learning theory with the classification model method. The system uses SVM toolbox to predict the output of training set, and establishes the mapping relationship between neural network parameters and observation data to form the support vector machine model. Through the use of SVM's own supervised learning algorithm to complete the fault state detection, and give the judgment results and display the operation, determine the optimal control strategy and other functions. The track circuit fault diagnosis method based on support vector machine (SVM) is a new technology. It can obtain all the information that may be marked to the noise in the classification samples by using a specific training set, so as to predict and identify the input patterns, and realize the abstraction, quantification and visualization of problem state description. At the same time, statistical analysis tools can also be used to obtain model parameters and automatically extract feature vectors [9-10].

2.2. Fault Diagnosis Design Scheme of Track Circuit

In the laboratory, the circuit has many states, such as conduction, open circuit, short circuit, etc. The track circuit is also a special circuit. The track circuit has three states: there is no car on the track, all equipment works normally, the track circuit works normally, and the track relay is pulled up (normally closed), which is called the adjustment state. When a train passes on the track circuit, it is similar to the short circuit state of the circuit. The train shunts, the voltage received by the track relay at the receiving end changes, and the track relay moving node drops reliably [11-12].

The track circuit plays a very important role in the railway signaling system. The main function of the track circuit is to supervise whether there is a train entering the track section, including whether there is a train running, whether shunting is in progress, etc., and to check the integrity of the track. Provide train operation information for the railway dispatching and command system by grasping and feeding back the train entering section and operation conditions [13-14].

The track circuit system is affected by many parameters in actual operation, which is a complex system with multiple inputs, multiple outputs, nonlinearity and strong coupling. For fault diagnosis of this kind of system, the input variables of the diagnosis system must be determined among many input parameters, mainly considering the following issues: first, the input variables must have a decisive impact on the output variables. Secondly, the input variables must be able to be measured directly or indirectly, and the accurate functional relationship between the results of the indirect measurement and the change law of the input variables can be established. Thirdly, it is required that the input variables can be measured online in real time or continuously. Other parameters that are not input variables can either have negligible impact on the system, or have an indirect impact on the system through the determined input variables [15-16].

After long-term investigation and research at the rail transport site, it is found that the following parameters in the track circuit system have an impact on the track circuit fault: the peak voltage of the wave head at the sending end, the rail surface voltage at the sending end, the rail surface voltage at the receiving end, the peak voltage of the wave head at the receiving end, the transmission frequency, the steel rail impedance, the ballast bed resistance, etc., which have an impact on the track circuit fault. The influencing parameters also include weather, such as temperature, air humidity, rainfall, snow thickness, etc. [17-18].

Common faults of track circuit are divided into red light band fault and poor shunting fault. The main reasons for the failure of the red light band of the track circuit are: the influence of the rail joint, the influence of the electrical insulation material, the influence of bad weather, the failure caused by external reasons, and the low voltage at the sending end of the track circuit itself, causing the track relay to fail to suck up. Bad shunting fault of track circuit: excessive shunting resistance, rail surface corrosion, dust pollution.

2.3. Comprehensive Fault Diagnosis of track Circuit Based on SA Algorithm

SA algorithm is a general probability algorithm, which is used to find the solution of the problem in a search space. The annealing process includes three processes. In the heating process, when the temperature reaches a certain level, the solid will dissolve into liquid, eliminating the uneven state when the solid form exists, and giving the next cooling process a starting point of equilibrium state. Isothermal process, solid at a certain temperature, the internal energy of any point in the body is equal everywhere. According to statistical mechanical analysis, the statistical properties of solid annealing process obey regular distribution:

$$Q = \frac{1}{R(S)} \exp\left(\frac{-F}{lS}\right) \tag{1}$$

Among them, $\exp\left(\frac{-F}{lS}\right)$ is called Bottzman factor and S is absolute temperature. R (S) is the standard factor of the probability distribution. The expression is as follows:

$$R(S) = \sum \exp\left(\frac{-F}{lS}\right) \tag{2}$$

The algorithm essentially consists of two loops. By slowly lowering the temperature, the algorithm may eventually converge to the global optimal solution.

3. Support Vector Machine Analog Circuit Fault Diagnosis Method Based on Privilege Information Fusion

3.1. Fault Diagnosis of Analog Circuit Based on Support Vector Machine with Privilege Information Fusion

According to the intelligent diagnosis method of analog circuits, the fusion of privilege information support vector machine algorithm for analog circuit fault diagnosis includes two stages: training stage and test diagnosis stage. See Figure 1 for details:

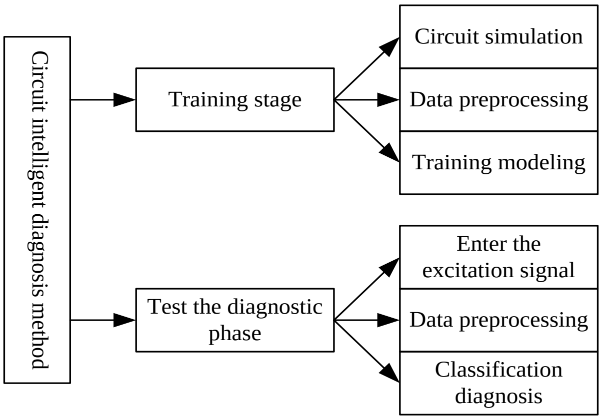

Figure 1. Intelligent diagnostic structure of the analog circuit

Training phase: first, schematic drawing and circuit simulation analysis of the circuit to be diagnosed shall be carried out, and the simulation shall include all possible fault modes as far as possible. Secondly, the sample data obtained from the simulation is preprocessed, and the feature extraction dimension reduction and feature selection are carried out through appropriate algorithms, so as to generate the data to be trained that is conducive to training classification. Finally, the data to be trained are input into the fused privilege information support vector machine for training modeling, and the final fused privilege information support vector machine model is determined through parameter optimization. Diagnosis stage: first, input appropriate excitation signal into the circuit to be diagnosed, extract the waveform to be diagnosed at the test point, conduct Monte Carlo sampling analysis on the waveform to be diagnosed, and extract the original sample to be diagnosed. Secondly, the original diagnosis pending samples are preprocessed, and the feature extraction dimension reduction and feature selection are carried out through appropriate algorithms, so as to generate the data to be diagnosed that is conducive to classification diagnosis. Finally, the data to be diagnosed are input into the trained model for classification diagnosis, and the recognition rate is calculated and the performance is analyzed.

The analog circuit fault diagnosis method of LUPI-SVM based on PCA feature extraction algorithm is as follows:

The fault feature vector is extracted from each sampling sample, and 20 groups of fault samples can be obtained for each fault after calculation. The binary tree LUPI-SVM is used to carry out multi class fault diagnosis for analog circuits, and the optimization problem is solved for class I problems with q training samples. Predict the fault category of the test sample.

3.2. Simulation Experiment

In this paper, ANFIS toolbox provided by MATLAB is used for simulation analysis. ANFIS generates a multi input single output system. The learning algorithms of ANFIS include back-propagation algorithm (BP algorithm) and least square method. We can use formula (3) to express the sample error:

$$F_q = \sum_{i=1}^{\sum(l-1)} (S_{i,q} - W_{i,q}^K)^2 \tag{3}$$

Wherein, $\sum(l-1)$ represents the total number of nodes in layer K, and $S_{i,q}$ represents the output of the qth sample to the ith component. The error gradient of network output is:

$$\frac{\lambda F_q}{\lambda W_{i,q}^K} = -2(S_{i,q} - W_{i,q}^K) \tag{4}$$

The back propagation algorithm and the least squares algorithm are combined to form a hybrid learning algorithm and applied in the whole training iteration. The least squares algorithm updates the parameters of the rule's successor, and the back propagation algorithm updates the parameters of the rule's predecessor.

3.3. Experimental Verification

According to the above diagnosis methods and specific implementation process for compensating capacitor fault and ballast resistance fluctuation, under laboratory conditions, set the simulation value of decision variables, and then use the support vector machine based algorithm diagnosis method to obtain the corresponding optimal value. Compare the simulation value and the optimal value to verify the correctness and feasibility of the fault diagnosis method.

4. Analysis of Experimental Results

4.1. Fault Recognition Rate Test of Different Support Vector Machines under Two Feature Extraction Algorithms

According to the samples, 50 to 300 samples are extracted, and then a variety of support vector machine methods are used for calculation. It is abbreviated as S-G, L-S, I-S, I+S-G and I+L-S. The fault identification rate tests of three support vector machines are shown in Table 1:

Table 1. Different SVM fault identification rate tests

	S-G	L-S	I-S	I+S-G	I+L-S
50	90	91.2	94.1	95.4	96.1
100	90.4	91.4	94.7	95.9	96.3
150	90.6	93.1	95.2	96.2	96.5
200	91.2	93.6	95.7	96.5	96.6
250	91.8	94.3	96	96.5	96.7
300	92	94.5	96.1	96.6	96.8

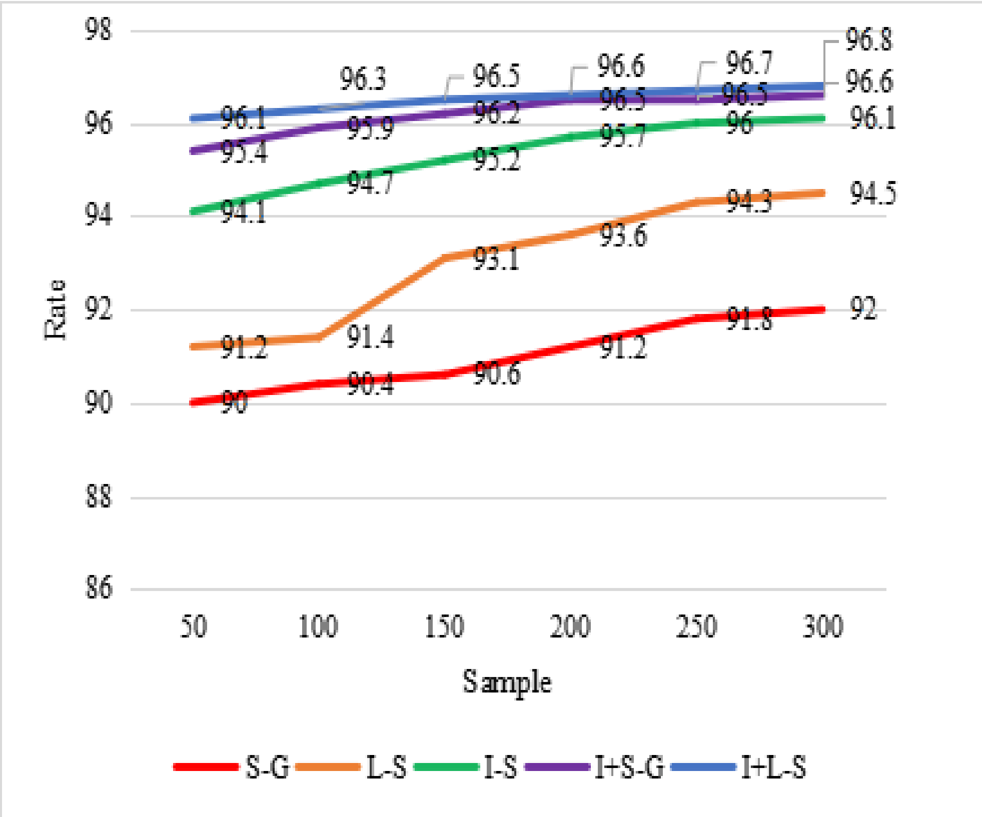

Figure 2. Different SVM fault identification rate tests

As shown in Figure 2, we can see that the test results show that the fault identification rate of the three support vector machines increases with the increase of the number of test samples. The fault identification rate of LUPI-SVM and SVM GA is much higher than that of using "PCA feature extraction algorithm" alone. In the same test sample case, LUPI-SVM is better than SVM GA, and SVM GA is better than SVM.

4.2. Fault Coverage and Diagnostic Identification Rate Test

In this paper, the above methods are used to test and diagnose the positioning of the whole machine to the unit circuit, the positioning of the unit circuit to the functional module, and the positioning of the functional module to the components for many times, and the fault coverage and fault identification rate are counted. See Table 2 for details:

Table 2. Fault coverage and diagnostic identification rate tests

	Total number of components	One fault component	Fault coverage
X1	60	58	96.7
X2	30	28	93.3
X3	20	20	100
X4	120	118	98.3
X5	220	218	99.1
X6	230	224	97.4

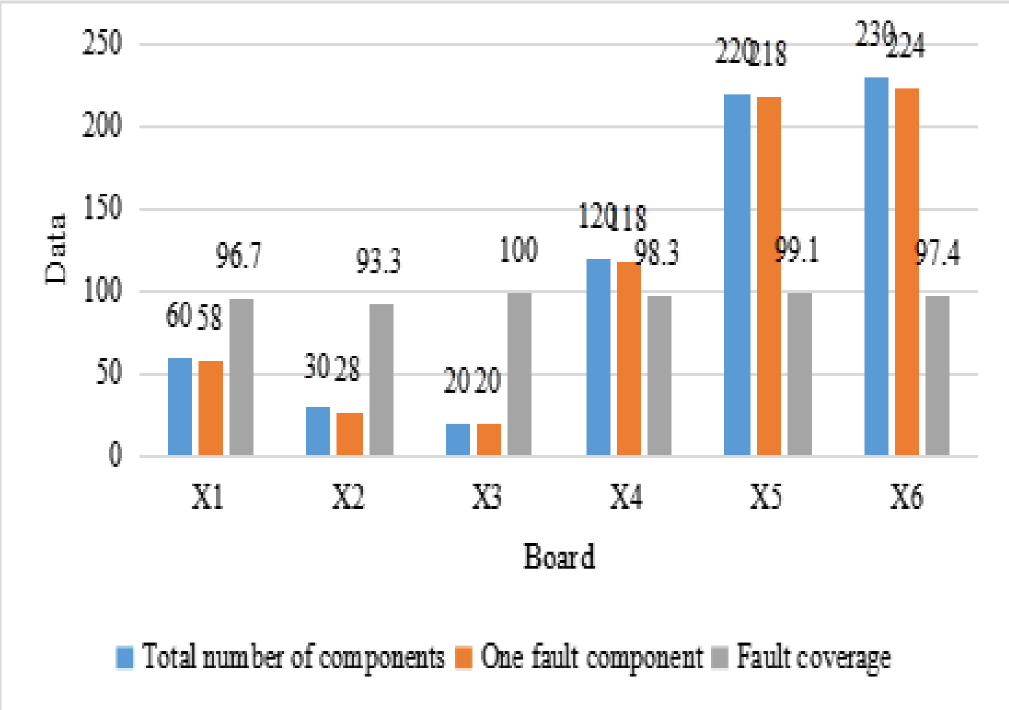

Figure 3. Fault coverage and diagnostic identification rate tests

As shown in Figure 3, from the fault identification rate, the diagnostic test of the ultrashort wave receiver using the method in this paper shows that the fault identification rate of one fault component is 97.4%, and the fault identification rate of the other fault components can reach 100%, while the fault identification rate of the other tone fault components is relatively low, 93.3%, which is also caused by different aging degrees of equipment and differences in circuit structures. It shows that this method has high fault identification rate and good test performance in the diagnosis test of this type of receiver.

5. Conclusion

In this paper, the track circuit fault diagnosis method is studied, and a support vector machine algorithm is designed. In the experiment, we also use SVM classifier to filter the signals. The model transforms the parameter estimation problem into a semi supervised learning process, and uses SVM training data for state assignment to achieve information extraction functions such as minimizing feature distance dimension. Finally, the simulation results show that this method can predict the track circuit faults well. However, due to limited conditions and slow training speed, the expected results were not achieved. In order to ensure convergence, stability and reliability, there are still some problems to be improved.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Hunter Goddard, Lior Shamir: SVMnet: Non-Parametric Image Classification Based on Convolutional Ensembles of Support Vector Machines for Small Training Sets. IEEE Access 10: 24029-24038 (2021). https://doi.org/10.1109/ACCESS.2021.3154405

[2] Sana Ullah Khan, Naveed Islam, Zahoor Jan, Khalid Haseeb, Syed Inayat Ali Shah, Muhammad Hanif: A Machine Learning-Based Approach for the Segmentation and Classification of Malignant Cells in Breast Cytology Images Using Gray Level Co-Occurrence matrix (GLCM) and Support Vector Machine (SVM). Neural Comput. Appl. 34(11): 8365-8372 (2021). https://doi.org/10.1007/s00521-021-05697-1

[3] Somya Goyal: Effective Software Defect Prediction Using Support Vector Machines (SVMs). Int. J. Syst. Assur. Eng. Manag. 13(2): 681-696 (2021). https://doi.org/10.1007/s13198-021-01326-1

[4] Mohd Mustaqeem, Mohd Saqib: Principal Component Based Support Vector Machine (PC-SVM): a Hybrid Technique for Software Defect Detection. Clust. Comput. 24(3): 2581-2595 (2021). https://doi.org/10.1007/s10586-021-03282-8

[5] Pooja Rani, Rajneesh Kumar, Anurag Jain: Coronary artery Disease Diagnosis Using Extra Tree-Support Vector Machine: ET-SVMRBF. Int. J. Comput. Appl. Technol. 66(2): 209-218 (2021). https://doi.org/10.1504/IJCAT.2021.119772

[6] Liaqat Ali, Iram Wajahat, Noorbakhsh Amiri Golilarz, Fazel Keshtkar, Syed Ahmad Chan Bukhari: LDA-GA-SVM: Improved Hepatocellular Carcinoma Prediction through Dimensionality Reduction and Genetically Optimized Support Vector Machine. Neural Comput. Appl. 33(7): 2783-2792 (2020). https://doi.org/10.1007/s00521-020-05157-2

[7] Saed Asaly, Lee-Ad Gottlieb, Yuval Reuveni: Using Support Vector Machine (SVM) and Ionospheric Total Electron Content (TEC) Data for Solar Flare Predictions. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 14: 1469-1481 (2021). https://doi.org/10.1109/JSTARS.2020.3044470

[8] Vinod Jagannath Kadam, Shivajirao M. Jadhav, Samir S. Yadav: Bagging Based Ensemble of Support Vector Machines with Improved Elitist GA-SVM features Selection for Cardiac Arrhythmia Classification. Int. J. Hybrid Intell. Syst. 16(1): 25-33 (2020). https://doi.org/10.3233/HIS-190276

[9] Samir D. Mehta, Ronnie Sebro: Computer-Aided Detection of Incidental Lumbar Spine Fractures from Routine Dual-Energy X-Ray Absorptiometry (DEXA) Studies Using a Support Vector Machine (SVM) Classifier. J. Digit. Imaging 33(1): 204-210 (2019). https://doi.org/10.1007/s10278-019-00224-0

[10] Akimasa Fujiwara, Makoto Chikaraishi, Diana Khan, Atsufumi Ogawa, Yoshihiro Suda, Toshikazu Yamasaki, Takaharu Nishino, Shutaro Namba: Autonomous Bus Pilot Project Testing and Demonstration using Light Rail Transit Track. Int. J. Intell. Transp. Syst. Res. 20(2): 359-378 (2021). https://doi.org/10.1007/s13177-021-00264-3

[11] Luigi Moccia, Duncan W. Allen, Gilbert Laporte, Andrea Spinosa: Mode Boundaries of Automated Metro and Semi-Rapid Rail in Urban Transit. Public Transp. 14(3): 739-802 (2021). https://doi.org/10.1007/s12469-021-00287-9

[12] Srinivas S. Pulugurtha, L. Prasanna Srirangam: Pedestrian Safety at Intersections Near Light Rail Transit Stations. Public Transp. 14(3): 583-608 (2021). https://doi.org/10.1007/s12469-021-00276-y

[13] Shahid Hussain, Faisal Khan, Wasiq Ullah, Basharat Ullah, Bakhtiar Khan: Development of a Low-Cost Modular Structure Fault Tolerant Field Excited Flux Switching Linear Machine for Urban Rail Transit. IEEE Access 9: 165854-165864 (2021). https://doi.org/10.1109/ACCESS.2021.3133299

[14] David Canca, José Luis Andrade-Pineda, Alicia De-Los-Santos, Pedro L. Gonzalez-R: A Quantitative Approach for the Long-Term Assessment of Railway Rapid Transit Network Construction or Expansion Projects. Eur. J. Oper. Res. 294(2): 604-621 (2021). https://doi.org/10.1016/j.ejor.2021.02.018

[15] Ali Shahabi, Sadigh Raissi, Kaveh Khalili Damghani, Meysam Rafei: Designing a Resilient Skip-Stop Schedule in Rapid Rail Transit Using a Simulation-Based Optimization Methodology. Oper. Res. 21(3): 1691-1721 (2019). https://doi.org/10.1007/s12351-019-00523-y

[16] Farah Asyikin Abd Rahman, Mohd Zainal Abidin Ab Kadir, Miszaina Osman, Ungku Anisa Ungku Amirulddin: Review of the AC Overhead Wires, the DC Third Rail and the DC Fourth Rail Transit Lines: Issues and Challenges. IEEE Access 8: 213277-213295 (2020). https://doi.org/10.1109/ACCESS.2020.3040018

[17] Sonu Mathew, Srinivas S. Pulugurtha: Assessing the Effect of a Light Rail Transit System on Road Traffic Travel Time Reliability. Public Transp. 12(2): 313-333 (2020). https://doi.org/10.1007/s12469-020-00234-0

[18] Arash Aziminejad, Yan He: Radio Communication in Curved Tunnels: MIMO Channel Capacity for Rail Transit Applications. IEEE Veh. Technol. Mag. 15(1): 99-106 (2020). https://doi.org/10.1109/MVT.2019.2960590