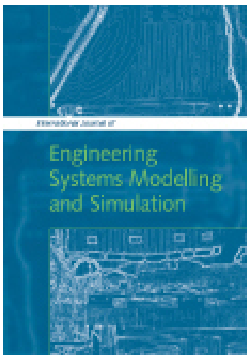



**International Journal of Engineering Systems Modelling and Simulation**

ISSN online: 1755-9766 - ISSN print: 1755-9758
https://www.inderscience.com/ijesms

---

# Visual exploration of fault detection using machine learning and image processing

D. Vijendra Babu, K. Jyothi, Divyendu Kumar Mishra, Atul Kumar Dwivedi, E. Fantin Irudaya Raj, Shilpa Laddha

**DOI:** 10.1504/IJESMS.2021.10043257

**Article History:**

| | |
|---|---|
| Received: | 30 July 2021 |
| Accepted: | 02 September 2021 |
| Published online: | 03 December 2022 |

# Visual exploration of fault detection using machine learning and image processing

## D. Vijendra Babu*

Department of Electronics and Communication Engineering,
Aarupadai Veedu Institute of Technology,
Vinayaka Mission's Research Foundation,
Paiyanoor, 603-104, Tamil Nadu, India
Email: drdvijendrababu@gmail.com
*Corresponding author

## K. Jyothi

Department of ECE,
College of Engineering Trikaripur, India
Email: jyothik@cetkr.ac.in

## Divyendu Kumar Mishra

Department of Computer Science and Engineering,
Faculty of Engineering,
VBS Purvanchal University Jaunpur,
Uttar Pradesh, India
Email: divyendu01mishra@gmail.com

## Atul Kumar Dwivedi

Department of ECE,
Bundelkhand Institute of Engineering and Technology,
Jhansi, India
Email: atuldwivedi@live.in

## E. Fantin Irudaya Raj

Department of Electrical and Electronics Engineering,
Dr. Sivanthi Aditanar College of Engineering,
Tamil Nādu, India
Email: fantinraj@gmail.com

## Shilpa Laddha

Department of Information Technology,
Government College of Engineering,
Aurangabad, Maharashtra, India
Email: kabrageca@gmail.com

**Abstract:** The machine learning CNN method defect detection is highly reliant on the training data; thus, post-classification regularisation may significantly improve the output. The suggested fault detection process may perform well on demanding synthetic and actual information by using a practical synthetic fault system depending on the SEAM model. We further propose the visual exploration be made more reliable regarding fault tolerance. The visual exploration model is made up of three-phase namely, visual identification and mapping, dynamic controller, and terminate criterion. The submap-dependent on visual mapping phase ensures higher mapping manageability, semantic classification dependent on active controller ensures continuous driving, and a new completion assessment technique ensures robust re-localisation under the terminate criterion. To preserve mapping and improve visual tracking, all the components are tightly linked. The proposed model machine learning CNN model is examined, and actual tests show fault-tolerance methods are proven to withstand visual monitoring and mapping failure situations.

**Keywords:** visual exploration; fault detection; convolutional neural networks; CNNs; image processing.

**Reference** to this paper should be made as follows: Babu, D.V., Jyothi, K., Mishra, D.K., Dwivedi, A.K., Raj, E.F.I. and Laddha, S. (2023) 'Visual exploration of fault detection using machine learning and image processing', *Int. J. Engineering Systems Modelling and Simulation*, Vol. 14, No. 1, pp.8–15.

**Biographical notes:** D. Vijendra Babu obtained his BE from the University of Madras, India, MTech from SASTRA, Tanjore, India and PhD from the Jawaharlal Nehru Technological University, Hyderabad, India. He is currently designated as the Vice Principal and a Professor in the Department of Electronics and Communication Engineering at Aarupadai Veedu Institute of Technology, Vinayaka Mission's Research Foundation, Deemed to be University. He has 22 years of experience in the field of education, research and administration at various levels. He has served as the HoD for 13 years. He has obtained grant for three Australian patents, one Indian design patent and published five Indian patents. He has published 90+ articles in referred international/national journals and conferences and also a reviewer in various leading journals/conferences.

K. Jyothi completed her MTech in Signal Processing and Embedded System and BTech in Electronics and Communication Engineering and her area of specialisations are signal processing and embedded system. She is working as an Assistant Professor in the Department of ECE in College of Engineering Trikaripur.

Divyendu Kumar Mishra received his PhD from the Wardha Central University, Maharashtra, India, in 2018. He currently works as an Assistant Professor at the Department of Computer Science and Engineering, VBS Purvanchal University Jaunpur, Uttar Pradesh, India. His current research interests include the natural language processing, IoT, machine learning and AI. He has more than five years of teaching experience and industry experience. He is an editorial board member of many national and international journals.

Atul Kumar Dwivedi received his MTech in VLSI Design at the VNIT Nagpur and PhD in specialisation of VLSI Signal Processing from the NIT Raipur. He always has shown meritorious performance in academics. He was associated with Tata Consultancy Services and Intel Corporation. He has worked in an advanced controller design lab at NIT Raipur and in National MEMS Design Centre NIT Nagpur. As an educator, he has worked as a faculty in BIT Durg. He is currently serving at BIET Jhansi. In addition to teaching and research, he is a coordinator of higher studies and employability training at institute level. He has received the top performing mentor award by NPTEL.

E. Fantin Irudaya Raj completed his BE in Electrical and Electronics Engineering, ME in Power Electronics and Drives, and currently pursuing his PhD degree from the Anna University, Chennai. Presently, he is working as an Assistant Professor at the Dr. Sivanthi Aditanar College of Engineering, Tamilnadu, India, and has more than ten years of teaching experience. He participated and presented his research ideas in more than 50 national and international conferences, published one book in the engineering series, contributed so many book chapters with various international publishers, and published more than 19 research articles in various international reputed journals. He is also acting as a reviewer for various international journals.

Shilpa Laddha is an Assistant Professor in the Department of Information Technology at Government College of Engineering, Aurangabad (Maharashtra). She holds a Doctorate (PhD) in Computer Science and Engineering. Her area of interest includes artificial intelligence, machine learning, information retrieval, semantic web mining and ontology and many more. She has a profound expertise in taking the full depth training of engineering students. She has three patents and two copyrights, to her credit and her many research papers are published in prominent international journals.

## 1 Introduction

Convolutional neural networks (CNNs) are coming under a supervised learning approach which may be built to handle a variety of hard issues in exploratory geophysics, thanks to their tremendous flexibility in network construction. Detection of specific seismic facies of concern is the easiest use of CNNs amongst such issues. CNN initially presented seismic information, wherein the CNN model is utilised to identify salt versus non-salt characteristics in a seismic volume (Waldeland and Solberg, 2017; Sabarinath et al., 2015). Around the identical time, claimed the fault detection process using CNN methods (Araya-Polo et al., 2017;

Huang et al., 2017). Faults are specific edges set in seismic information from the standpoint of computer vision (CV).

With remarkable effectiveness, CNN is highly applicable to more broad edge detection issues (El-Sayed et al., 2013; Xie and Tu, 2015). Faults in seismic information, on the other hand, are significantly distinct from edges in pictures utilised in CV. With a typical computerised vision image, areas isolated by edges are largely homogenous, but in seismic information, these areas are characterised using reflector patterns. Furthermore, all seismic edges information faults.

Conventional edge identification qualities like coherence are vulnerable to stratigraphic edges like disconformities, channel banks, as well as karst collapsing in practicality while giving great fault pictures (Marfurt et al., 1999). An excellent methodology for autonomously generating fault surfaces is developed in which calculating the fault likelihood is a critical stage (Wu and Hale, 2016). To produce these fault likelihood levels, fault detection approaches depending on CNN may be utilised as an option, and thus, the fault striking, and dipping can be calculated using the fault likelihood.

The applications depending on the vision include visual exploration, which is critical. Several similar types of research in the visual simultaneous localisation and mapping (VSLAM) field are published for visual identification and mapping, with a priority on precision (Mur-Artal and Tardós, 2015; Forster et al., 2014). As stated, (Cadena et al., 2016) improving robustness might be a significant barrier for realistic vision-based navigation systems, and several types of research are published to address this issue (Bourmaud and Megret, 2015; Lin et al., 2018). Nonetheless, to solve the challenge by addressing vision-dependent navigation as a fault-tolerant mechanism, in which both driving as well as exploration termination platforms are addressed, in contrast to prior research which approaches reliability improvement as a CV problem. A fault-tolerance framework is presented here, based on (AbuKhalil et al., 2015; Ding et al., 2017), in which a ‘fault’ is characterised as a collapse of visual monitoring as well as mapping.

Numerous issues, regarding VSLAM, must be addressed for fault-tolerance in autonomous mobile robots (Lussier et al., 2005; Upasana et al., 2015). The construction of a dynamic controller for the mobile application to identify the required motion is however challenging. The platform for mobile localisation is often necessary for controls (Lauri and Ritala, 2016). Several comparable studies use a Homograph transformation to find the target point in the picture space (Arrospide et al., 2010; Pears and Liang, 2001), which requires a planar premise, which restricts the controller’s applicability and robustness. A reactive technique based on the acquired picture is presented in the latest decades of great development in pattern recognition (Long et al., 2015; Krizhevsky et al., 2012) studies, and this is widely explored in the autonomous driving field (Fang et al., 2005; Sotelo et al., 2004; Sidhwani et al., 2014).

To test the efficacy of the suggested methodology, both actual synthetic information and field information is employed. The synthetic data must preferably be a close match to field data that allow complete control over the parameter collection. From the impedance method, sub-volumes are being selected and adding faults, thus, synthetic data depending on the SEAM model is created (Fehler and Larner, 2008). The suggested fault identification method, which produces highly clear fault pictures, shows tremendous promise in both synthetic information and field information.

## 2 Background and related works

Arrhythmia diagnosis requires automated ECG data analysis. It is owing to the extensive usage of portable ECG equipment like the Holter monitoring that generates a lot of information that must be processed. In specific, autonomous ECG data analysis consists of two key stages namely extracting feature and beat categorisation (Pal and Majumder, 2010). Arrhythmia detection programs (De Chazal et al., 2004) use the outcomes of such processes to identify arrhythmias. The collection of ECG features is critical for accurate heartbeat categorisation and cardiac disorders diagnosis, particularly in the analysis of long-term observations (Karpagachelvi et al., 2010). With ECG data, several extraction methods as well as signal transformation strategies are suggested, which may be classified as time-domain, frequency-domain, and time-frequency domain methods. For instance, RR-intervals retrieved by a sliding window are used in one very effective time-domain arrhythmia categorisation method (Tsipouras et al., 2005). Symbolic aggregate approximation (SAX) is a method for classifying heartbeats relying on a symbolic depiction of ECG data (Lin et al., 2007). The method namely frequency-domain is used to develop an arrhythmia detection system that extracts frequency-domain information through the fast Fourier transformation (Gothwal et al., 2011). Wavelet transforms are used to create a hybrid heart rate identification system that maintains both time-domains as well as frequency-domain information (Zhao and Zhang, 2005).

Spatiotemporal visualisation: all earthquakes as well as observing information are considered spatiotemporal along with multivariate informational data. To show spatiotemporal data, a variety of visualisations have been developed. A simple, but straightforward three-dimensional visualisation metaphor is the space-time cubes. In the spatiotemporal scenario, relevant glyphs are utilised to represent multivariate data (Tominski et al., 2012). Several studies explicitly encode temporal data (Andrienko and Andrienko, 2011) and also multivariate data on a two-dimensional map to minimise visual clutter caused by the three-dimensional display (Bak et al., 2009). Filtering, grouping, and aggregation techniques are used to make spatiotemporal data easier to explore and analyse (Krüger et al., 2013; Andrienko et al., 2009; Andrienko and Andrienko, 2008). To evaluate multivariate spatiotemporal data, VIS-STAMP uses methods including connected parallel coordinates and SOM (Guo et al., 2006). Furthermore, a toolbox is used as a statistical approach to forecasting hotspot areas (Maciejewski et al., 2011; Ganesh Babu et al., 2021). Currently, there has been a lot of talk about spatiotemporal heterogeneous data analysis. The VASA system suggested a pipeline to explore the relationship between traffic, weather, and crucial infrastructure modelling (Ko et al., 2014; Sridevi et al., 2021).

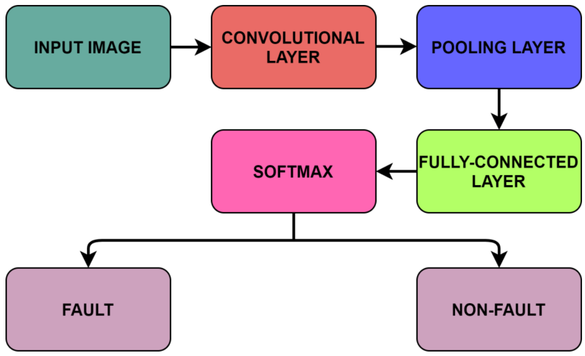
Describing processing techniques for the seismic picture to produce maps of the fault probability, checking those maps for incorrect fault detection, and applying discrete surfaces across the regions of higher fault likelihood is all part of autonomous fault interpretation. In the research (Wu and Hale, 2016; Wu and Zhu, 2017), realistic procedures for autonomous fault interpretation are outlined, as well as instances of successful applications. These procedures, though, have yet to be implemented into the standard software industry. Obtaining high-quality maps of fault chances is an important part of an efficient workflow for autonomous fault interpretation. Various options are used, which were eventually depending on attributes deduced effectively from seismic information (Di et al., 2018; AlRegib et al., 2018), however, in recent decades, image processing, as well as artificial intelligence concepts, are applied to this search area (Lu et al., 2018; Bharath Kumar et al., 2021).

## 3 Proposed workflow

A CNN classifier has been utilised to generate a fresh image of defects in the suggested process. We use a three-dimensional CNN model depending on a patch to classify every seismic sample wherein the samples are utilised from a three-dimensional window. Figure 1 illustrates the CNN framework utilised in this work. Many convolutional layers, pooling layers, and then fully-connected layers make up a basic CNN model depending on the patch. A CNN model collects a few higher-level image abstractions (identical to seismic data) utilising the convolutional layer and pooling layers after that categorise the obtained data utilising the fully connected layers, which also perform similarly to a conventional multilayer perceptron networking, provided a three-dimensional patch of seismic magnitudes. The network's result is a singular value reflecting the facies labelling of the seismic sample focused at the three-dimensional patch. This labelling is binary in this research, meaning 'defect' or 'non-fault.'

The defect pictures are then improved using a variety of image processing methods. To calculate the fault's azimuth, dip, and magnitude, initially directional Laplacian of Gaussian (LoG) filter is used to boost high-angle lineaments acquired from layered reflectors and reduce anomalies near to reflector dip. Then, the skeletonisation phase is used to re-distribute fault anomalies inside a fault damage state to the nearest feasible fault plane using such data. Next, some thresholding is performed to get a binary picture of the defects. When this output remains noisy, a median filter is employed to decrease the random noise then apply the directed LoG with iterative skeletonisation until acquiring a satisfactory result.

**Figure 1** CNN framework (see online version for colours)

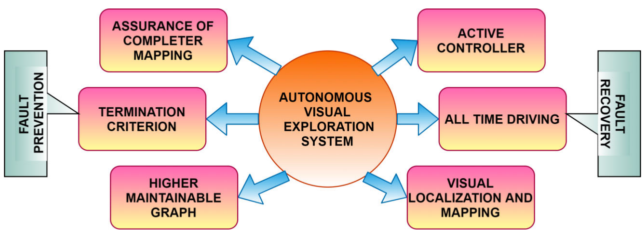



Initially, put the suggested procedure to the examination using synthetic information generated using the SEAM model. The enhanced SEAM model with stacked channels as well as turbidites gives the model a reasonable representation of actual data collected. To create seismic volumes, the fault is injected randomly in the impedance modelling to convolve using a Ricker wavelet of 40 Hz. The list of parameters was utilised randomly of five reverse faults in the three-dimensional volume. Because of the turbidites present in the model, a significant layer distortion with amplitude changes across reflectors in this proposed model. As a result of the presence of various forms of discontinuities, these synthetic data provide a significant challenge to a fault detection system. The softmax function is described as follows

$$softmax(x_i) = \frac{\exp(x_i)}{\sum_j (x_j)} \tag{1}$$

Here, $x_i$ is the $i^{th}$ vector element and $x_j$ is denoted as $j^{th}$ vector element of the proposed model.

**Figure 2** Structure of visual exploration system (see online version for colours)

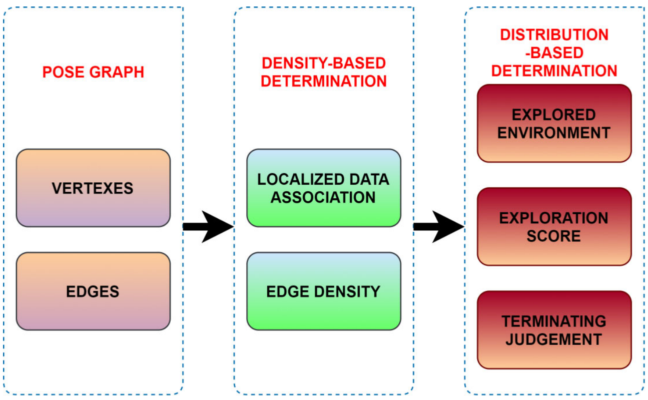



The active controller has been the initial unit in the architecture, as illustrated in Figure 2. For efficient robotic exploration, a controller is being developed which can function independently of global localisation and continuing motion, allowing for failure recovery in terms of hardware control. To address the vulnerability of visual localisation, this type of controller is presented. Localisation is required for path planning in most current controllers. Owing to the sensitivity of visual exploration, it is difficult to attain complete localisation every time. The system employs a reactive technique that allows it to accomplish ground identification from a given picture. Two claims are taken for ground identification without sacrificing generalisation: the monocular camera is pointed in the mobile platform's directional heading, and the camera is set at a pitch that allows the bottom to be seen plenty of time. The pre-trained model Pascal contextual is used in the system, and the result is a partitioned picture of the identical size as the provided input image. Furthermore, this partitioning does not require any previous information or localisation.

### 3.1 *Visual localisation and mapping (VLM)*

Architecture is built in the VLM front-end for exact visual recognition within every new keyframe through evaluating several restrictions simultaneously, resulting in an adequate outcome. Furthermore, to reduce the number of keyframes, a multiple-layer keyframe selection has been implemented. In this scenario, fault prevention is the most important front-greater end's frame rating. The creation of loop-closure restrictions is sped up using a parallel architecture. The construction of the restrictions is split into many threads as well as executed in parallel. The frame rate may be enhanced utilising this technique that is directly proportionate to the amount of created restrictions. Map maintainability should increase with a greater frame rate.

**Figure 3** The proposed organisation (see online version for colours)




A multi-layer technique is devised enabling keyframe selection. The initial stage is to calculate the optical-flow length; the next is to calculate the global descriptive variance across all keyframes. An initially enhanced optical-flow technique is utilised to compute the visual length among the present frame as well as the final keyframe before descriptive collection as the descriptive collection is a time-consuming process. The global description of the present picture has to be retrieved for keyframe selections as well as referenced frame identification once the image meets a resemblance criterion. By reducing the time it takes to retrieve the descriptors, including a selection approach can save time.

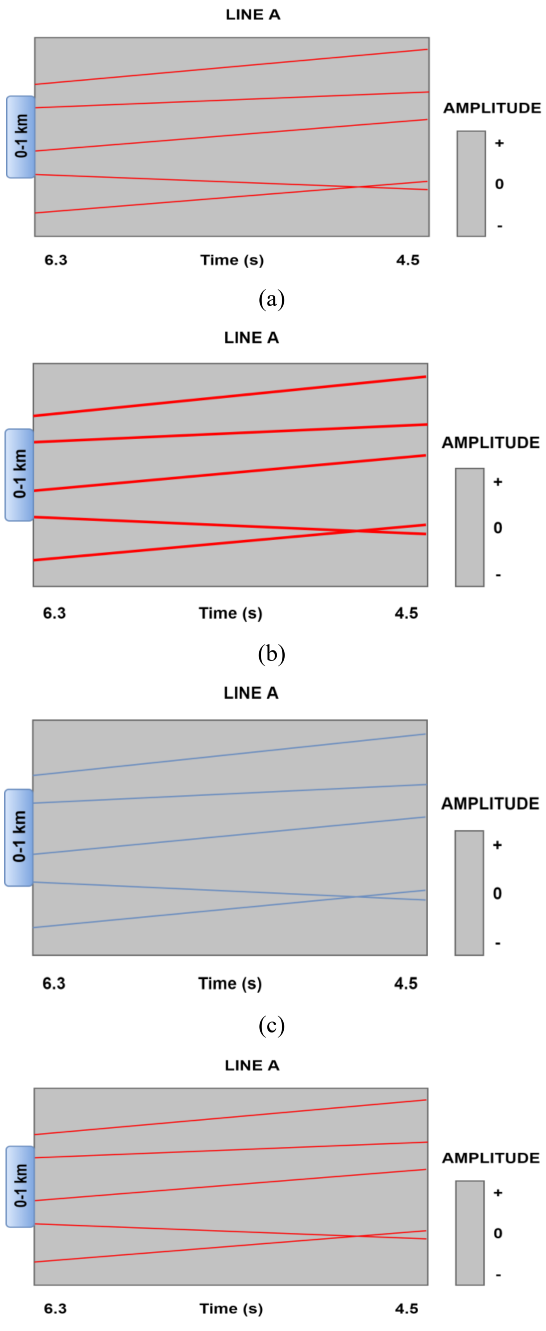
The terminating criterion is examined once environment modelling in VLM establishes the mapping's completion. Because the investigated space is restricted in internal exploration, a terminating criterion is required. The map data has been assured to be comprehensive sufficient for robust re-localisation via adequate determination. The geographical density and then collected keyframes distribution may be used to assess mapping completion according to the visual exploration system based on keyframes. The suggested terminating criterion is organised as shown in Figure 3, with coarse completeness determined using the localised keyframe density with fine complete determination using the keyframes distribution globally. The density-based complete assessment is done initially in this mechanism to get the number of participants for the statistics distribution-based determination in phase.

## 4 Performance analysis

CNN model is trained randomly to utilise 20% of fault plane samples as well as the identical number of non-fault samples. The produced synthetic data is displayed on a single line, with errors indicated in red is shown in Figure 4(a). Similar to Figures 4(a) and 4(b) depicts the CNN-based fault detector's actual outputs and the faults show as a tiny zone rather than as sticks. There are occasional misclassifications when data is difficult to get by, as is to be assumed. The regularisation processes are then carried out. The outcome of the directed LoG filter, as well as skeletonisation, is shown in Figure 4(c). The flaws are thinner and relatively continuous as a result of those two processes, which are removed a lot of the noise. Lastly, thresholding is used to create a fault map with faults labelled as '1' in which they occur and '0' in which they do not as shown in Figure 4(d).

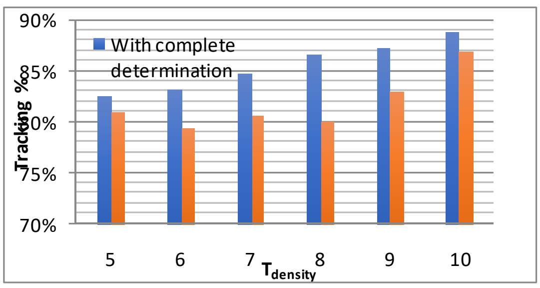
The experiment's purpose is to assess the thoroughness of the examination. To assess the effect of the suggested technique, two sets of trials are established, using tracking percentages in case of with as well as without complete determination recorded. A $T_{density}$ series is also supplied, and the exploration time for satisfying the terminating criterion is observed, whereas the mapping without completion determination is ended based on its recorded time. Figure 5 depicts the outcome of the visual exploration in both cases. A greater tracking percentage indicates that the investigation has progressed with completion determination. We investigate the influence of complete determination on visual exploration under the terminating criterion. Figure 5 shows the improvement brought about by complete determination, which shows a greater visual exploration %.

**Figure 4** (a) Artificially created fault lines, (b) CNN fault detection outcome, (c) Fault detection after LoG and skeletonisation and (d) Fault detection after thresholding (see online version for colours)




(a) (b) (c) (d)

**Figure 5** Complete determination of visual exploration of fault detection (see online version for colours)




## 5 Conclusions

This study proposes fault detection architecture for reliable visual exploration for tracking and mapping. In environmental analysis, a VLM are utilised, with a parallel layout as well as a back-end depending on submap is added will enable mapping and monitoring. Furthermore, a separate active controller for global localisation has been created. In this paper, we present a fault detection approach that employs both CNN-based categorisations with image processing regularisation. CNN classifier has been trained to exclusively detect faults, substantially reducing the mixture of faults and encounters other discontinuity in the fault images obtained. We next utilise a regularisation procedure based on image processing to augment the fault-planes and then reduce non-fault characteristics in the fresh fault images. Either of tough synthetic information and field information, the suggested methodology demonstrates significant promise. The efficacy of our method is confirmed via experiments. Thus, a viable remedy to fault tolerance is proposed through fault prevention and recovery for dependable visual exploration.

## References

AbuKhalil, T., Sobh, T. and Patil, M. (2015) 'Survey on decentralized modular robots and control platforms', in *Innovations and Advances in Computing, Informatics, Systems Sciences, Networking, and Engineering*, pp.165–175, Springer, Berlin/Heidelberg, Germany.

AlRegib, G., Deriche, M., Long, Z., Di, H., Wang, Z., Alaudah, Y., Shafiq, M.A. and Alfarraj, M. (2018) 'Subsurface structure analysis using computational interpretation and learning: a visual signal processing perspective', *IEEE Signal Process. Mag.*, Vol. 35, No. 2, pp.82–98, http://dx.doi.org/10.1109/MSP.2017.2785979.

Andrienko, G.L. and Andrienko, N.V. (2008) 'Spatio-temporal aggregation for visual analysis of movements', in *Proc. of IEEE VAST*, pp.51–58.

Andrienko, G.L., Andrienko, N.V., Rinzivillo, S., Nanni, M., Pedreschi, D. and Giannotti, F. (2009) 'Interactive visual clustering of large collections of trajectories', in *Proc. of IEEE VAST*, pp.3–10.

Andrienko, N.V. and Andrienko, G.L. (2011) 'Spatial generalization and aggregation of massive movement data', *IEEE Trans., Vis. Comput. Graph.*, Vol. 17, No. 2, pp.205–219.

Araya-Polo, M., Dahlke, T., Frogner, C., Zhang, C., Poggio, T., and Hohl, D. (2017) 'Automated fault detection without seismic processing', *The Leading Edge*, Vol. 36, No. 3, pp.208–214, https://doi.org/10.1190/tle36030208.1.

Arrospide, J., Salgado, L., Nieto, M. and Mohedano, R. (2010) 'Homography-based ground plane detection using a single onboard camera', *IET Intell. Transp., Syst.*, Vol. 4, No. 2, pp.149–160.

Bak, P., Mansmann, F., Janetzko, H. and Keim, D.A. (2009) 'Spatiotemporal analysis of sensor logs using growth ring maps', *IEEE Trans. Vis. Comput. Graph.*, Vol. 15, No. 6, pp.913–920.

Bharath Kumar, R., Suresh, P. and Hemakumar, V.S. (2021) 'Automated anesthesia level controller using fuzzy logic for injectable type', *Journal of Applied Science and Engineering*, Vol. 24, No. 5, pp.749–755.

Bourmaud, G. and Megret, R. (2015) 'Robust large scale monocular visual SLAM', in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Boston, MA, USA, 7–12 June, pp.1638–1647.

Cadena, C., Carlone, L., Carrillo, H., Latif, Y., Scaramuzza, D., Neira, J., Reid, I. and Leonard, J.J. (2016) 'Past, present, and future of simultaneous localization and mapping: toward the robust-perception age', *IEEE Trans. Robot*, Vol. 32, No. 6, pp.1309–1332.

De Chazal, P., O'Dwyer, M. and Reilly, R.B. (2004) 'Automatic classification of heartbeats using ECG morphology and heartbeat interval features', *IEEE Transactions on Biomedical Engineering*, Vol. 51, No. 7, pp.1196–1206.

Di, H., Wang, Z., AlRegib, G. et al. (2018) 'Why using CNN for seismic interpretation? An investigation', in *2018 SEG International Exposition and Annual Meeting*', Society of Exploration Geophysicists, pp.2216–2220.

Ding, K.., Morozov, A. and Janschek, K. (2017) 'Classification of hierarchical fault-tolerant design patterns', in *Proceedings of the 15th International Conference on Pervasive Intelligence & Computing, 3rd International Conference on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/ CyberSciTech), 2017 IEEE 15th International Conference on Dependable, Autonomic and Secure Computing*, Orlando, FL, USA, 6–10 November, pp.612–619.

El-Sayed, M.A., Estaitia, Y.A. and Khafagy, M.A. (2013) 'Automated edge detection using convolutional neural network', *International Journal of Advanced Computer Science and Applications*, Vol. 4, No. 10, pp.11–17, https://doi.org/ 10.14569/ijacsa.2013.041003.

Fang, Y., Dixon, W.E., Dawson, D.M. and Chawda, P. (2005) 'Homography-based visual servo regulation of mobile robots', *IEEE Trans. Syst. Man Cybern. Part B Cybern. A Publ. IEEE Syst. Man Cybern. Soc. 2005*, Vol. 35, pp.1041–1050.

Fehler, M. and Larner, K. (2008) 'SEG advanced modeling (SEAM), phase I first-year update', *The Leading Edge*, Vol. 27, No. 8, pp.1006–1007, https://doi.org/10.1190 /1.2967551.

Forster, C., Pizzoli, M. and Scaramuzza, D. (2014) 'SVO: fast semi-direct monocular visual odometry', in *Proceedings of the 2014 IEEE International Conference on Robotics and Automation (ICRA)*, Hong Kong, China, 31 May–7 June, pp.15–22.

Ganesh Babu, O., Danya, T.R., Sakthieswaran, N., Suresh, P. and Muthuraman, U. (2021) 'Sustainable characteristics of fly ash based geopolymer concrete incorporating alccofine, zeolite and rubber fibers', *Revista Română de Materiale/Romanian Journal of Materials*, Vol. 51, No. 1, pp.17–24.

Gothwal, H., Kedawat, S. and Kumar, R. (2011) 'Cardiac arrhythmias detection in an ECG beat signal using fast Fourier transform and artificial neural network', *Journal of Biomedical Science and Engineering*, Vol. 4, No. 4, p.289.

Guo, D., Chen, J., MacEachren, A.M. and Liao, K. (2006) 'A visualization system for space-time and multivariate patterns (VIS-STAMP)', *IEEE Trans. Vis. Comput., Graph*, Vol. 12, No. 6, pp.1461–1474.

Huang, L., Dong, X. and Clee, T.E. (2017) 'A scalable deep learning platform for identifying geologic features from seismic attributes', *The Leading Edge*, Vol. 36, No. 3, pp.249–256, https://doi.org/10.1190/tle36030249.1.

Karpagachelvi, S., Arthanari, M. and Sivakumar, M. (2010) *ECG Feature Extraction Techniques – A Survey Approach*, arXiv preprint arXiv: 1005.0957.

Ko, S., Zhao, J., Xia, J., Afzal, S., Wang, X., Abram, G., Elmqvist, N., Kne, L., Van Riper, D., Gaither, K., Kennedy, S., Tolone, W., Ribarsky, W. and Ebert, D.S. (2014) 'VASA: interactive computational steering of large asynchronous simulation pipelines for societal infrastructure', *IEEE Trans. Vis. Comput. Graph*., Vol. 99, No. 12, pp.1853–1862

Krizhevsky, A., Sutskever, I. and Hinton, G.E. (2012) 'ImageNet classification with deep convolutional neural networks', in *Proceedings of the International Conference on Neural Information Processing Systems*, Lake Tahoe, NV, USA, 3–6 December, pp.1097–1105.

Krüger, R., Thom, D., Wörner, M., Bosch, H. and Ertl, T. (2013) 'Trajectory lenses – a set-based filtering and exploration technique for long-term trajectory data', *Comput. Graph. Forum*, Vol. 32, No. 3, pp.451–460.

Lauri, M. and Ritala, R. (2016) 'Planning for robotic exploration based on forward simulation', *Robotics and Autonomous Systems*, Vol. 83, pp.15–31, ISSN 0921-8890, https://doi.org /10.1016/j.robot.2016.06.008.

Lin, J., Keogh, E., Wei, L. and Lonardi, S. (2007) 'Experiencing SAX: a novel symbolic representation of time series', *Data Mining and Knowledge Discovery*, Vol. 15, No. 2, pp.107–144.

Lin, X., Chen, W., He, L., Guan, Y. and Liu, G. (2018) 'Improving the robustness of monocular VT&R system with multiple hypotheses', in *Proceedings of the IEEE International Conference on Robotics and Biomimetics*, Macau, China, 5–8 December, pp.355–360.

Long, J., Shelhamer, E. and Darrell, T. (2015) 'Fully convolutional networks for semantic segmentation', in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Boston, MA, USA, 7–12 June, pp.3431–3440.

Lu, P., Morris, M., Brazell, S., Comiskey, C. and Xiao, Y. (2018) 'Using generative adversarial networks to improve deep-learning fault interpretation networks', *Lead. Edge*, Vol. 37, No. 8, pp.578–583, http://dx.doi.org /10.1190/tle37080578.1.

Lussier, B., Lampe, A., Chatila, R., Guiochet, J., Ingrand, F., Killijian, M.O. and Powell, D. (2005) 'Fault tolerance in autonomous systems: how and how much?', in *Proceedings of the 4th IARP-IEEE/RAS-EURON Joint Workshop on Technical Challenges for Dependable Robots in Human Environments (DRHE)*, Nagoya, Japan, 16–18 June.

Maciejewski, R., Hafen, R., Rudolph, S., Larew, S.G., Mitchell, M.A., Cleveland, W.S. and Ebert, D.S. (2011) 'Forecasting hotspots – a predictive analytics approach', *IEEE Trans. Vis. Comput. Graph.*, Vol. 17, No. 4, pp.440–453.

Marfurt, K.J., Sudhaker, V., Gersztenkorn, A., Crawford, K.D. and Nissen, S.E. (1999) 'Coherency calculations in the presence of structural dip', *Geophysics*, Vol. 64, pp.104–111, https://doi.org/10.1190/1.1444508.

Mur-Artal, R.M.J.M.M. and Tardós, J.D. (2015) 'ORB-SLAM: a versatile and accurate monocular SLAM system', *IEEE Trans. Robot*., Vol. 31, No. 5, pp.1147–1163.

Pal, S. and Majumder, S. (2010) *ECG Data Analysis, In Intelligent Medical Technologies and Biomedical Engineering: Tools and Applications*, pp.122–144, IGI Global, India.

Pears, N. and Liang, B. (2001) 'Ground plane segmentation for mobile robot visual navigation', in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, Maui, HI, USA, 29 October–3 November, Vol. 3, pp.1513–1518.

Sabarinath, R. and Markkandan, S. (2015) 'Complexity analysis and performance comparison of channel decomposition methods used in MIMO precoder design', *International Journal of Applied Engineering Research (IJAER)*.

Sidhwani, S., Malkotiya, M., Korde, N., Unde, S.B. and Salunke, M. (2014) 'Autonomous driving: using a vision-based approach', *Int. J. Comput. Appl.*, Vol. 92, pp.20–24.

Sotelo, M.A., Rodriguez, F.J., Magdalena, L. et al. (2004) 'A color vision-based lane tracking system for autonomous driving on unmarked roads', *Autonomous Robots*, Vol. 16, pp.95–116, https://doi.org/10.1023/B:AURO.0000008673.96984.28.

Sridevi, R., Kumar, C., Suresh, P., Ganesan, S., Subramanian, S. and Suresh, A. (2021) 'Development of a pedagogical framework to analyze the performance of induction machines', *International Journal of Electrical Engineering and Education*, Vol. 58, No. 2, pp.501–516.

Tominski, C., Schumann, H., Andrienko, G.L. and Andrienko, N.V. (2012) 'Stacking-based visualization of trajectory attribute data', *IEEE Trans. Vis. Comput. Graph.*, Vol. 18, No. 12, pp.2565–2574.

Tsipouras, M.G., Fotiadis, D.I. and Sideris, D. (2005) 'An arrhythmia classification system based on the RR-interval signal', *Artificial Intelligence in Medicine*, Vol. 33, No. 3, pp.237–250.

Upasana, S., Markkandan, S. and Venkateswaran, N. (2015) 'Centralized and decentralized precoding frame work in multiuser – MIMO wireless communication', *Advances in Natural and Applied Sciences*, *AENSI Journal*, Special edition, Vol. 9, No. 6, pp.478–485.

Waldeland, A.U. and Solberg, A.H.S.S. (2017) 'Salt classification using deep learning', *79th Annual International Conference and Exhibition, EAGE, Extended Abstracts*, *Tu-B4-12*, https://doi.org/10.3997/2214-4609.201700918.

Wu, X. and Hale, D. (2016) '3D seismic image processing for faults', *Geophysics*, Vol. 81, No. 2, pp.IM1–IM11, https://doi.org/10.1190/geo2015-0380.1.

Wu, X. and Zhu, Z. (2017) 'Methods to enhance seismic faults and construct fault surfaces', *Computers & Geosciences*, Vol. 107, pp.37–48, ISSN 0098-3004, https://doi.org/10.1016/j.cageo.2017.06.015.

Xie, S. and Tu, Z. (2015) 'Holistically-nested edge detection', *Proceedings of the IEEE International Conference on Computer Vision*, pp.1395–1403.

Zhao, Q. and Zhang, L. (2005) 'ECG feature extraction and classification using wavelet transform and support vector machines', in *International Conference on Neural Networks and Brain*, IEEE, Vol. 2, pp.1089–1092.