

High Impedance Fault Detection Based on Attention Mechanism and Object Identification

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Abstract—Detection of high impedance faults (HIFs) has been traditionally a main challenge in the protection of distribution systems, since they do not generate enough current to be reliably detected by conventional over-current relays. Data-based methods are alternative HIF detection methods which avoid threshold settings by training a classification or regression model. However, most of them lack interpretability and are not compatible with various distribution networks. This paper proposes an object detection-based HIF detection method, which has higher visualization and can be easily applied to different scenarios. First, based on the analysis of HIFs, a Butterworth band-pass filter is designed for HIF harmonic feature extraction. Subsequently, based on the synchronized data provided by distribution-level phasor measurement units, global HIF feature gray-scale images are formed through combining the topology information of the distribution network. To further enhance the feature information, a locally excitatory globally inhibitory oscillator region attention mechanism (LEGIO-RAM) is proposed to highlight the critical feature regions and inhibit useless and fake information. Finally, an object detection network based You Only Look Once (YOLO) v2 is established to achieve fast HIF detection and section location. The obtained results from the simulation of the proposed approach on three different distribution networks and one realistic distribution network verify that the proposed method is highly effective in terms of reliability and generalization.

Index Terms—Attention mechanism, distribution-level phasor measurement units, high impedance faults, object detection.

I. INTRODUCTION

HIGH impedance faults (HIFs) are specific types of faults in distribution systems which primarily occur when conductors of overhead power lines break and touch poorly conductive surfaces, such as soil, sand, concrete, tree limb, etc. The HIFs often perform as arcing grounded faults with unstable and low fault currents, which are hard to be detected by traditional overcurrent relays. Accurate and reliable HIF detection has become an urgent need for safe power supplies,

concerning the risk of equipment damages, fire hazards, and even human injury [1].

To effectively identify HIFs in distribution networks, distinctive HIF feature extraction is a critical link in fault detection. The HIF feature extraction methods can be basically classified into model-based and transform-based methods. The model-based feature extraction approaches focus on describing and deducing the behavior of varying electrical quantities by the model establishment which are divided into two methods, i.e., neutral grounding-sensitive and HIF type-sensitive. The type of neutral grounding-sensitive methods aim at HIF feature extraction in one or several neutral grounding modes, including isolated neutral [2] and [3], resonant neutral [3] and [4], and low-resistor-earthed neutral [5]. The HIF type-sensitive methods concentrate on the effect of different surfaces, such as vegetation HIFs [6], soil-grounding HIFs [7], underwater cable HIFs [8], etc. Even though the model-based methods have good performance under certain circumstances, they lack sufficient generalization.

Contrarily, transform-based methods extract and enhance the more general features of HIFs by applying and combining mathematical transform algorithms, including wavelet transform (WT) [9], Stockwell transform (ST) [10], [11], Hilbert-Huang transform (HHT) [11], [12], and variational mode decomposition (VMD) [13]. In addition to these transform domain methods, the applications of other transform algorithms are also explored for feature extraction, such as mathematical morphology (MM) [14], [15], which can express the waveform distortions generated by HIF nonlinearities. These transform-based methods can strip and amplify the difference of HIFs from different aspects, but the corresponding traditional HIF detection methods with fixed threshold settings have relatively low reliability. As a result, threshold-free methods based on machine learning (ML) algorithms have received increased attention from researchers.

ML-based methods achieve HIF detection by training a classification or regression model using historical feature data. Most ML-based HIF detection methods adopt supervised learning (SL) algorithms. Neural network (NN) is a broad category in SL algorithms, which has been applied in HIF detection in many various forms, such as artificial neural network (ANN) [16], probabilistic neural network (PNN) [10], convolutional neural network (CNN) [17], etc. Additionally, decision trees [6] and support vector machines (SVMs) [18], [19] are two typical SL algorithms, which have relatively simple structures and are easy to train. However, due to the

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lack of available historical data, the practical application of these SL-based methods is difficult. To improve the feasibility and practicality of ML-based methods, some researchers have proposed different approaches. A semi-supervised learning (SSL)-based HIF detection method is proposed by using a combination of a small set of labeled data and other unlabeled data to reduce the required amount of training data [20]. In [21], the authors proposed a transfer learning-based method under a cloud-edge collaboration framework to achieve HIF detection with a small amount of actual data in a target situation by integrating data of different distribution networks. In general, ML-based methods have shown great potential in the field of HIF detection but still need improvements in their generalization to different distribution networks.

Most of the existing ML-based HIF detection methods are split into two individual parts: feature extraction and detection model establishment. These ML detection models only focus on feature data and predict corresponding labels but lack sufficient interpretability. In a sense, this is an important reason why these ML models have weak performance in different distribution networks. Recently, some ML algorithms with better interpretability, such as graph neural network (GNN), which can better adapt to topology changes by taking system topology into account [22], have been applied to fault detection. In this paper, an object detection-based HIF detection method is proposed. The proposed approach establishes a topology-related feature by using global synchronized information. Based on the enhanced features, an object detection network is trained for identifying HIFs and locating the corresponding region. Combining with the regional map, the proposed method can simultaneously achieve HIF detection and section location with good interpretability and generalization. Based on the analysis, a Butterworth band-pass filter is designed for HIF harmonic feature extraction. Through the synchronized measurement generated by distribution-level phasor measurement units (D-PMUs), the global synchronized features are formed by combining with topology information. To enhance feature regions and inhibit the useless or fake information, a locally excitatory globally inhibitory oscillator region attention mechanism (LEGIO-RAM) is proposed. Finally, an object detection network is designed based on You Only Look Once (YOLO) v2 and trained for HIF detection and region location. The performance of the proposed method was verified with simulation and practical data.

This remainder of this paper is organized as follows: The topology-related HIF feature extraction is introduced in Section II. In Section III, LEGIO-RAM is proposed and explained in detail. In Section IV, the YOLO v2 object detection network is presented and designed. Section V provides the setting of the verification scenarios, and the verification results are shown, compared, and explained. Finally, conclusions are drawn in Section VI.

II. TOPOLOGY-RELATED HIF FEATURE EXTRACTION

A. Analysis with HIFs and Filter Design

HIFs always perform as nonlinear arcing, which causes the distortions of the current waveform. One of the typical HIF

nonlinear characteristics is periodic “zero-off”, which means the distortions appear at the stage near the zero-crossing in stable situations [23]. It is due to the fact that the low current levels in this period cause a decrease in arc ionization. The arc resistance increases and the distortions are exhibited. With the rise of voltage after zero, the arc resistance decreases and the current distortions gradually recover. As a result, the “zero-off” phenomenon tends to make the current waveform parallel to the horizontal axis [1], [24].

To analyze the zero-off phenomenon, an ideal equivalent HIF F_{eq} is established, as shown in Fig. 1(a). It can be seen that the equivalent zero-off distortion brings a series of declining odd harmonics. By comparing them with the spectrum of different real HIFs (as shown in Fig. 1(b)–(d)), the distortions are shown to be primarily contributed by 3rd harmonic components. Meanwhile, the currents of real HIFs include other high-frequency components and inter-harmonics [25]. Therefore, to extract the zero-off distortions of HIF, a band-pass filter is designed to extract the main harmonic contributors.

To maintain the 3rd harmonic components and avoid the extra distortions, we choose a Butterworth filter in feature extraction. The frequency response of the Butterworth filter is flat in the passband and roll-offs towards zero in the stopband without causing any ripple. The rate of roll-off response depends on the order of the filter. The frequency response of the N^{th} order low-pass Butterworth filter is given as:

$$H(j\omega) = \frac{1}{\sqrt{1 + C^2 \left(\frac{\omega}{\omega_p}\right)^{2N}}} \quad (1)$$

where C is a constant parameter. ω is angular frequency, and ω_p is cutoff frequency. The transfer function $H(p)$ is expressed as:

$$H(p) = \frac{1}{(p - p_1)(p - p_2) \cdots (p - p_N)} \quad (2)$$

where $p = j(\omega/\omega_p)$ and $p_h = e^{j\frac{2h+N-1}{2N}\pi}$, $h = 1, 2, \dots, N$. The corresponding transfer function $H(s)$ with normalization removing can be written as:

$$H(s) = H(p)|_{p=\frac{s}{\omega_p}} \quad (3)$$

The transfer function of the band-pass Butterworth can be transferred by the low-pass Butterworth as follows:

$$H_{bp}(s) = H\left(\frac{s^2 + \omega_l\omega_u}{s(\omega_l - \omega_u)}\right) \quad (4)$$

where ω_l and ω_u are lower cutoff frequency and upper cutoff frequency, respectively. Based on the FDATool of Matlab, the number of order N is designed as 4, $\omega_l = 87.83$ Hz, and $\omega_u = 184.44$ Hz (the frequency of fundamental harmonic is 50 Hz). This filter can not only retain the key harmonic components but also eliminate the effect of high-frequency components (above 3rd order) and measurement noises. By removing the fundamental harmonic component, the zero-off distortions of HIFs can be effectively extracted and amplified.

Due to the impact of the predominant 3rd harmonic component, the extracted features of fault branches have a noticeable

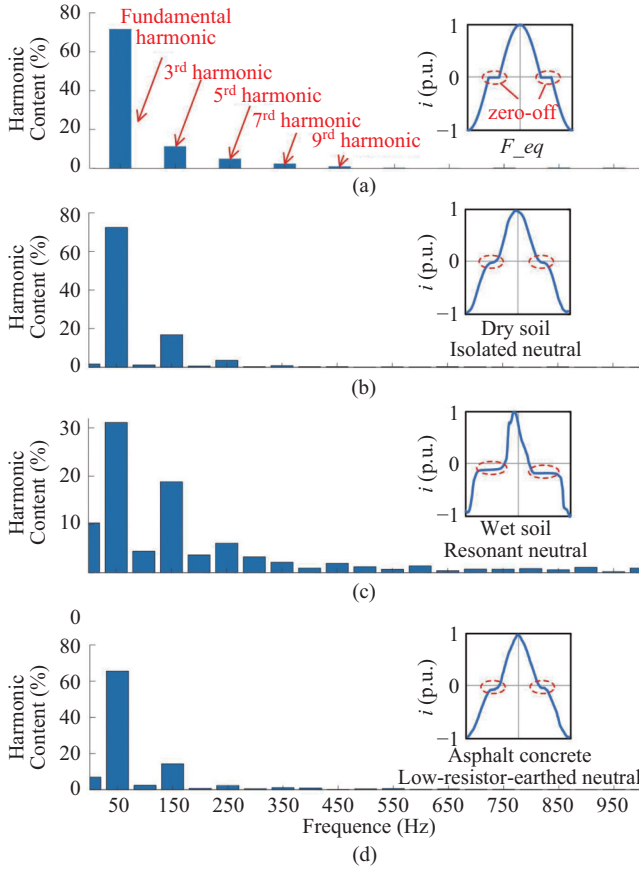


Fig. 1. The Fourier spectrum analysis results. (a) Ideal equivalent general waveform. (b) A dry soil grounding HIF in an isolated neutral network. (c) A wet soil grounding HIF in a resonant neutral network. (d) An asphalt concrete grounding HIF in a low-resistor-earthed neutral network.

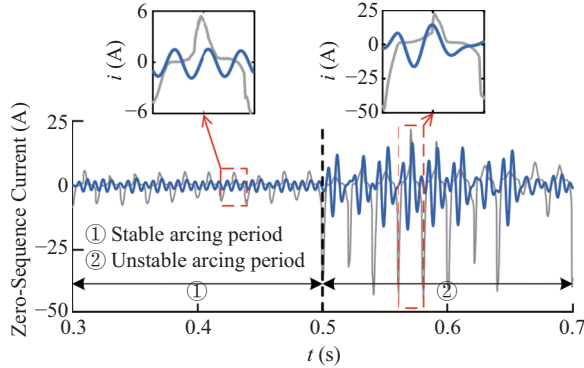


Fig. 2. The extracted feature of a dry soil grounding HIF in a resonant neutral network and the “three peaks” phenomenon per cycle.

“three peaks” characteristic in one cycle. As shown in Fig. 2, taking a dry soil grounding HIF in a resonant neutral network (a 10 kV 50 Hz actual experiment distribution network shown in Fig. 7(c) and described in Section V.C) as an example, it can be seen that the “three peaks” is obvious and well-distributed in the stable arcing period. By comparison, because of the effect of 2nd harmonic and inter harmonics, the features in the unstable arcing period have some distortions but still show the “three peaks” phenomenon.

In distribution networks, the 3rd harmonic currents are

primarily produced by unbalanced non-linear loads, such as a single-phase rectifier with capacitive filtering. The common sources of 3rd harmonics include TV, microwave ovens, micro-computers, printers, and switch mode power supplies (SMPS). These devices are mostly connected in low-voltage (LV) distribution networks, which causes the three-phase imbalance and 3rd harmonics [26]. However, in most countries, such as Europe and China, the ungrounded wirings of stepdown transformers lead to the isolation of the medium-voltage (MV) distribution network from loads at the LV side [23]. Therefore, behaviors at the load or DG side do not affect the zero-sequence current at the MV network. Meanwhile, considering the cost of D-PMUs, the proposed method is more suitable in MV distribution networks.

B. Topology-related Global HIF Feature

The extracted feature of a particular frequency band has two main restrictions in practical applications: data quality and limited amplitude values. Traditional measurements in distribution networks cannot provide reliable data with sufficient sampling frequency. The development of D-PMUs brings significant improvement in the measurement level. D-PMUs can provide high sampling-rate three-phase voltage and current phasor data with less error, and all the measurements are GPS time-stamped. D-PMU devices provided by different manufacturers may vary in terms of measurement variables, sampling rate, and data accuracy and precision. The D-PMUs employed in this article were developed by a project supported by the Chinese government. The sampling rate is 6,400 samples per second, and the amplitude error is less than 0.2%. Moreover, the zero-sequence currents are provided. Based on the measurements provided by D-PMUs, the data quality can satisfy the requirement of feature extraction.

HIFs generally have higher than 600 Ω resistance and produce low-level fault current. Based on verification results, the amplitude of the extracted feature is between 1/5 and 1/2 of the original waveform, which makes that threshold-based detection method hard to adapt. In this paper, we establish a topology-related HIF feature with synchronized data provided by D-PMUs. Through this topology-related feature, the “three peaks” characteristic of HIF can be effectively highlighted.

To form the HIF feature, a regional map corresponding to the distribution network is designed first based on the topology and the position of the D-PMUs. Taking a 20-node distribution network given in Fig. 3(a) as an example, its region map is shown as a square in total. The principles are listed as follows:

1) *Direction*: the direction from left to right corresponds to the head to the end of the topology. Sequential regions from left to right are connected topologically.

2) *Multi-terminal*: for a multi-terminal node, the height of each outgoing region is equally divided from the forward region.

3) *Region widths*: The sum of widths of regions corresponding to any parallel outgoing lines are the same. The width of the minimum region is determined by the average division of regions which have maximum amounts of sequential regions.

As a result, if D-PMUs are located at each node, the region map is shown in Fig. 3(b). If D-PMUs are located as the

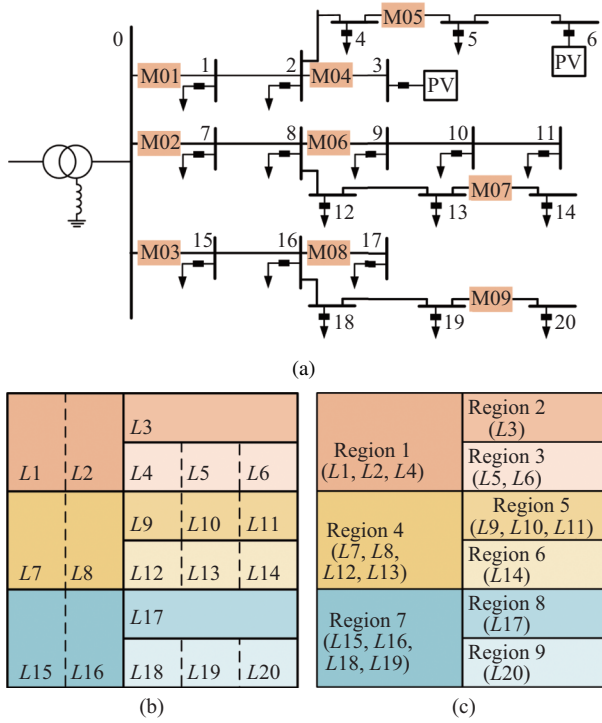


Fig. 3. The topology and corresponding region maps of a 20-node distribution network. (a) The topology. (b) The region map when D-PMUs are located in all nodes. (c) The region map when D-PMUs are located as the (a) shown.

Fig. 3(a) shown, the region map becomes Fig. 3(c).

The data of each region is calculated by the extracted features of the zero-sequence current in Section II.A. Let $\mathbf{I}f_x$ represent the extracted feature vector of D-PMU(x). The region r is represented as a $h \times w$ matrix $\mathbf{R}_r$. There are three different situations to define the regions:

(1) If region $\mathbf{R}_{r-1}$ is two-ended and both ends have D-PMUs (represented by a and b), the region is defined as:

$$\mathbf{R}_{r-1}(h^1, w^1) = \mathbf{I}f_a(h^1) - w^1 \cdot \frac{d(\mathbf{I}f_a(h^1) - \mathbf{I}f_b(h^1))}{dw} \quad (5)$$

where w^* and h^* belong to $[1, w]$ and $[1, h]$, respectively.

(2) If region $\mathbf{R}_{r-2}$ is multi-ended and all ends have D-PMUs (represented by a and b_1-b_n), the region is defined as:

$$\begin{aligned} \mathbf{R}_{r-2}(h^2, w^2) \\ = \mathbf{I}f_a(h^2) - w^2 \cdot \frac{d(\mathbf{I}f_a(h^2) - \sum_{b=b_1}^{b_n} \mathbf{I}f_b(h^2))}{dw} \end{aligned} \quad (6)$$

(3) If region $\mathbf{R}_{r-3}$ only have one D-PMU at the head, the region is defined as (let $\mathbf{I}f_b(h^3) = 0$):

$$\mathbf{R}_{r-3}(h^3, w^3) = \mathbf{I}f_a(h^3) - w^3 \cdot \frac{d(\mathbf{I}f_a(h^3) - \mathbf{I}f_b(h^3))}{dw} \quad (7)$$

Assuming that the whole region map is $L \times L$, L is determined by the lowest height $\min(h_{1-n})$, equal to the sampling number under the default time window. In this paper, the time window is set as 128 sampling points, which corresponds to one cycle under the sampling rate 6,400 Hz. According to principle (3), w of each region is calculated by L . After the

whole region map is filled, all data are globally normalized to $[255, 0]$. In this way, the synchronized features of the distribution network are transformed to a topology-related global HIF feature gray-scale image. There are three main benefits to form the feature gray-scale image. First, globally combining and normalizing the extracted synchronized features can effectively highlight the HIF characteristics. Secondly, the topology-related characteristics can simultaneously provide the HIF alarm and fault location by comparison of the corresponding region maps in the final detection. Thirdly, the HIF feature gray-scale image can avoid the misjudgments caused by the distortion of original waveform data, extracted “three peaks” characteristics, or the small-amplitude similar characteristics in healthy lines (if waveform data are utilized directly for the object detection model described in Section IV.A).

Figure 4 shows an example of a feature image corresponding to the region map in Fig. 3(b). It can be seen that the “three peaks” characteristic of HIF is shown as three dark strips in corresponding regions. By identifying this feature and comparing it with the region map, the HIF regions can be determined.

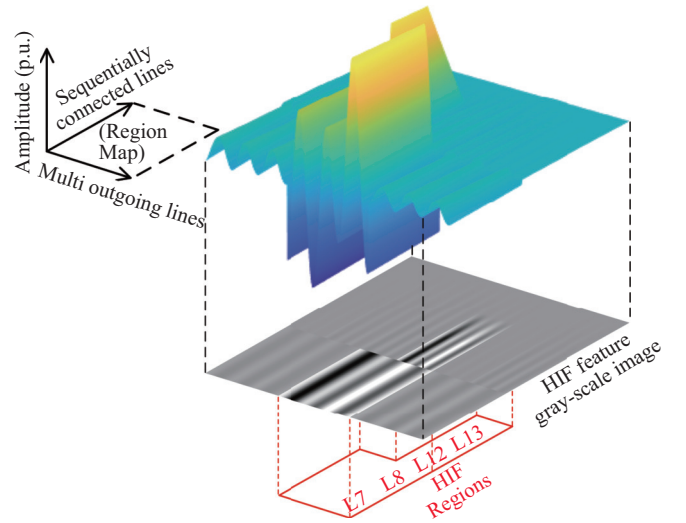


Fig. 4. The 3-dimensional feature sketch, HIF feature gray-scale image, and the matched fault regions of a HIF in L13 in the 20-node distribution network.

III. INTRODUCTION OF LEGIO-RAM

The proposed topology-related feature gray-scale image adopts global normalization to determine the value of each pixel. However, because the “three peaks” characteristics shape oscillates around zero, the normalized non-fault regions also show off non-ignorable gray values. When the “three peaks” characteristics appear as distortions along the y-axis, the non-fault regions may bury the key regions’ information. In addition, when the distribution network is in a normal or disturbance situation, the extracted features will display useless information. As a result, in this paper, the attention mechanism is introduced which solves this problem by providing regions with different attention weights. The attention mechanism provides receivers with the ability to focus on the useful subset of inputs, which has been introduced in deep learning and achieved effectiveness.

This paper proposes an attention mechanism called LEGIO-RAM, which can enhance the key regions and inhibit useless or fake information. This attention mechanism is inspired by a locally excitatory globally inhibitory oscillator network (LEGION) [27]. The core of this method is to achieve synchronization within a locally coupled oscillator assembly and desynchronization between different assemblies through relaxation oscillators. LEGIO-RAM is a two-layer structure network, which can generate inter-region and intra-region soft attention weights. The inter-region attention weight of each region i corresponds to the oscillator $O_i(x_i, y_i)$, where x_i is an excitatory and y_i is an inhibitory. x_i is defined as follows:

$$\frac{dx_i}{dt} = 3x_i - x_i^3 + 2 - y_i + \rho + I_i + S_i \quad (8)$$

The differential of x_i contains a cubic function to achieve oscillation. The parameter ρ is the amplitude of Gaussian noise, which can better engender the separation of synchronized groups of oscillators; I_i is an external stimulus. When $I_i > 0$, the O_i is stimulated and unstimulated if $I_i \leq 0$; S_i reflects the coupling with other oscillators, including excitation from neighboring oscillators O_j ($j \in N_i$) and inhibition from a global inhibitor z , which is defined as:

$$S_i = \sum_{j \in N_i} W_{ij} H(x_j - \zeta_x) - W_z H(z - \zeta_z) \quad (9)$$

where N_i includes the number of neighboring oscillators within a fixed distance. Both ζ_x and ζ_z are thresholds. W_{ij} represents a connection weight determined by excitation between O_i and O_j . $H(*)$ is a Heaviside step function defined as $H(a) = 1$ if $a \geq 0$ and $H(a) = 0$ if $a < 0$. W_z is the weight of inhibition from the global inhibitor z , which is defined as:

$$\frac{dz}{dt} = \phi(\sigma_\infty - z) \quad (10)$$

where ϕ is a parameter. σ_∞ is equal to one if $x_i \geq \theta_x$ and zero otherwise. The inhibitory of y_i is defined as follows:

$$\frac{dy_i}{dt} = \varepsilon \left(\gamma \left(1 + \tanh \frac{x_i}{\beta} \right) - y_i \right) \quad (11)$$

where ε is a very small positive parameter. $1 + \tanh(x_i/\beta)$ is an activation function. The parameter γ determines the proportion of the time in active or inhibited phase. The larger γ is, the shorter is the period of the active phase.

The process can be described as follows: When an oscillator moves into the active phase, it will trigger the inhibition for the entire network by the global inhibitor z . Meanwhile, this oscillator will propagate its excitation to its neighbors and continue to propagate to further neighbors. Therefore, the network can achieve synchronization between similar oscillators and desynchronization between different oscillators.

The second layer of LEGIO-RAM is to determine intra-region soft attention. The oscillators in this layer correspond to all pixels in each active region. The main difference of this layer is the introduction of lateral potential to better eliminate noise from the key area of the pixels. The excitatory x_m of $O_m(x_m, y_m)$ is defined by the equation as follows:

$$\frac{dx_m}{dt} = 3x_m - x_m^3 + 2 - y_m + \rho$$

$$+ I_m H(P_m + e^{-\alpha t} - \zeta) + S_m \quad (12)$$

Variable P_m denotes the lateral potential of the oscillator, which is determined by the activities of its neighbors under a certain distance. The P_i is defined as:

$$\frac{dP_m}{dt} = \lambda(1 - P_m) H \left[\sum_{n \in N'_m} T_{mn} H(x_n - \zeta_x) - \zeta_p \right] - \mu P_m \quad (13)$$

where $\lambda > 0$ and T_{mn} is a permanent connection weight of O_m and O_n . If the activity x_n of neighbor $n \in N'_m$ satisfies $x_n > \zeta_x$, T_{mn} is accumulated. If the sum of accumulated T_{mn} is greater than ζ_p , P_m will grow its value to one by the term $\lambda(1 - P_m)$. If $H(*) = 0$, the lateral potential will reduce to zero with rate μ . The introduction of P_m makes the noise pixels in the neighbor N'_m be inhibited by the leader oscillator O_m . Except for the lateral potential, other structures are the same as the first layer.

The inputs of both layers are defined as follows: For the first layer, according to the region map, the whole feature gray-scale image can be divided into $e \times f$ areas based on the smallest width and height: $e = L/\min(h)$ and $f = L/\min(w)$. Let $v(x, y)$ be the pixel value of coordinate (x, y) in the image and belong to the area $A(e_1, f_1)$, the input of the first layer $R(x, y)$ is defined as the information entropy of its corresponding area:

$$R(x, y) = R(A) = \sum_{v \in A} p_v \ln p_v \quad (14)$$

where p_v is the probability of occurrence of pixel value v .

The output of the first layer is the asynchronous groups of regions. The k regions of one same group θ share an obvious similarity. So, the attention map of first layer Γ^1 is:

$$\Gamma^1(R(x, y)) = \begin{cases} \kappa, & g(\theta) = \min(g) \\ 1, & g(\theta) > \min(g) \end{cases} \quad (15)$$

$$g(\theta) = \frac{1}{k} \sum_{A \in \theta} R(A)$$

where κ is an inhibition parameter that belongs to $(0, 1)$.

The input of the second layer is the pixels of each active region ($\Gamma^1(R(A)) = 1$). Similarly, we define that the group θ' , including k' pixels are formed by the second layer. The attention map of the second layer Γ^2 is:

$$\Gamma^2(v(x, y)) = \frac{1}{1 + e^{-\kappa' g'(v)}}$$

$$g'(v) = \frac{1}{k'} \sum_{v \in \theta'} v(x, y) \quad (16)$$

Subsequently, a Sigmoid function is introduced to convert the pixel value of the group multiplied by parameter k into the attention map value. As a result, the final attention map Γ is defined by:

$$\Gamma(x, y) = \Gamma^1(R(x, y)) \cdot \Gamma^2(v(x, y)) \quad (17)$$

Through the proposed LEGIO-RAM, the key regions will be highlighted with the inhibition of useless regions, and the information of these key regions will become enhanced. The

structure of LEGIO-RAM is shown in Fig. 5. In the LEGIO-RAM, N_i in layer 1 is set as 4, and set as 24 in layer 2. In layer 2, N'_m is set as 8 and $\zeta_p = 16$. For the parameters of attention mechanism, $\kappa = 0.1$ and $\kappa' = 0.1$ (pixel values is normalized to $[0, 1]$) Other main parameters are list here: $I_i = 0.2$, $\rho = 0.02$, $W_{ij} = 2.5$, $W_z = 1.5$, $\zeta_x = -0.5$, $\zeta_z = 0.1$, $\varepsilon = 0.02$, $\phi = 3$, $\gamma = 6.5$, $\beta = 0.1$, $\alpha = 0.05$, $\lambda = 0.1$, $T_{mn} = 2$.

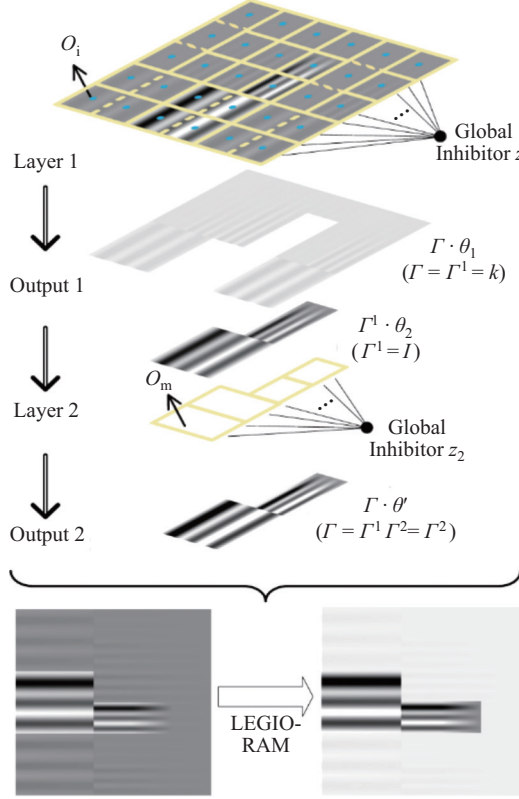


Fig. 5. The whole structure of LEGIO-RAM.

IV. YOLO v2 OBJECT DETECTION ALGORITHM AND THE WHOLE HIF DETECTION PROCEDURE

A. YOLO v2 Object Detection Algorithm

Based on the extracted and enhanced HIF feature image, the last step of HIF detection is to detect and locate the HIF regions. Object detection can achieve these two tasks at the same time. There are several mature object detection networks, including spatial pyramid pooling Net (SPPNet), Faster R-CNN, and YOLO. In this paper, YOLO v2 [28] is selected, since it has a relatively fast detection speed and good accuracy and can satisfy the requirement of HIF detection. YOLO v2 is a typical one-stage target detection network, which means it requires only a single pass through the neural network and predicts all the bounding boxes in one go, as shown in Fig. 6.

A YOLO v2 network comprises two subnetworks: a feature extraction network followed by a detection network. For the input scales, YOLO v2 resizes the input resolution to $[416, 416]$ to generate a single center cell by setting an odd number of region locations. Through the down-sampling of the input,

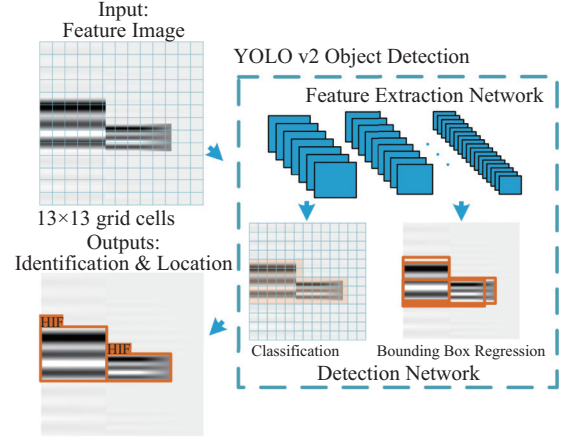


Fig. 6. YOLO v2 framework for object detection.

the size of the final resolution is 13×13 . There is no fully-connected layer in YOLO v2, which is replaced by introducing anchor boxes to predict bounding boxes. To obtain better performance, the k-means dimension cluster is used to train the bounding boxes.

The YOLO v2 network includes 23 layers. The feature extraction network adopts Darknet-19 [25], and the feature becomes $W_y \times H_y \times (N_y \times 5 + C)$, where W_y and H_y are the width and height of the output feature. N_y is the number of bounding boxes B and C is the number of classes. The predicted bounding box B can be represented by $(b_x, b_y, b_w, b_h, b_o)$, which can be calculated by:

$$\begin{aligned} b_x &= \sigma(t_x) + c_x, \quad b_y = \sigma(t_y) + c_y \\ b_w &= p_w e^{t_w}, \quad b_h = p_h e^{t_h}, \quad b_o = \sigma(t_o) \end{aligned} \quad (18)$$

where (c_x, c_y) is the top left coordinate of the cell, and $(b_x/W_y, b_y/H_y)$ is the center of B relative to the whole image. $(t_x, t_y, t_w, t_h, t_o)$ represent the offset of the corresponding coordinates from the actual B . $\sigma(*)$ denotes the Sigmoid function. $b_w \times b_h$ is the size of the bounding box relative to the bounding box prior (p_w, p_h) . The loss function is defined as:

$$\begin{aligned} \text{loss}_t &= \lambda_{\text{noobj}} \sum_{i=0}^{W_y-1} \sum_{j=0}^{H_y-1} \sum_{k=0}^{B_y-1} \sum_{l=0}^{\text{noobj}} b_{oijk}^2 \\ &+ \lambda_{\text{obj}} \sum_{i=0}^{W_y-1} \sum_{j=0}^{H_y-1} \sum_{k=0}^{B_y-1} \sum_{l=0}^{\text{obj}} \text{IoU}(B_{\text{pred}}, B_{gt}) I_{ijk}^{\text{obj}} (1 - b_{oijk})^2 \\ &+ \lambda_{\text{class}} \sum_{i=0}^{W_y-1} \sum_{j=0}^{H_y-1} \sum_{k=0}^{\text{obj}} I_{ijk}^{\text{obj}} \sum_{c \in \text{classes}} \text{MSE}(C) \\ &+ \lambda_{\text{coord}} \sum_{i=0}^{W_y-1} \sum_{j=0}^{H_y-1} \sum_{k=0}^{B_y-1} \sum_{l=0}^{\text{obj}} (2 - w_{gt} h_{gt}) \prod_{ijk}^{\text{obj}} (b_x - b'_x)^2 \\ &+ (b_y - b'_y)^2 + (t_w - t'_w)^2 + (t_h - t'_h)^2. \end{aligned} \quad (19)$$

where the loss function has four terms: no-object, object, class, and matched loss. $\text{IoU}(b, \text{object})$ is the intersection over union (IoU) between the predicted result and the ground truth object, which is defined as $\text{IoU}(b, \text{object}) = |b \cap \text{object}| / |b \cup \text{object}|$. I_{ijk}^{noobj} and I_{ijk}^{obj} mean the confidence value of the k^{th} B in

location (i, j) , which is determined by the IoU is lower than a pre-set threshold T_{pre} or not. I_{ij}^{obj} denotes if the object is in location (i, j) . $\text{IoU}(B_{pred}, B_{gt})$ is the IoU between predicted and ground truth B . MSE means the mean squared error loss. And the last term calculates the coordination loss with the location information. Where, (w_{gt}, h_{gt}) is the relative location value of the B . $(b'_x/W_y, b'_y/H_y)$ is the center coordinate for the ground truth B . (t'_w, t'_h) is the natural logarithm of the size of (p_w, p_h) . The structure of the network is the same as [28]. The parameters are set as follows: $\lambda_{noobj} = 1$, $\lambda_{obj} = 5$, $\lambda_{class} = 1$, $\lambda_{coord} = 1$. T_{pre} is set as 0.6.

After training the YOLO v2 network, the output is the predicted bounding boxes with confidence values. Here, we choose the bounding boxes with higher than 0.75 confidence. Then, calculate every $\text{IoU}(B_{result}, R_{ri})$ and choose the regions with a higher than 0.6 IoU value as the final determined regions. Finally, a confirmation method called reasonableness check is adopted here: if there is a y -coordinate existing in all the determined regions, and the x -coordinate ranges of regions are all connected, the result is TRUE; otherwise, it is FALSE. To avoid misjudgements for the individual transient process, such as potential 3rd harmonic provided by switching in/out of capacitor, we consider that at least 4 continuous TRUE results as a confirmed HIF. Note that in the period of short-time intermittent arcing of HIFs, which just maintains 1 or 2 cycles, the proposed method cannot give effective alarms until they develop into continuous HIFs.

B. The Whole HIF Detection Procedure

Till now, the details of the proposed HIF detection method have been described. In summary, a flowchart of the whole detection procedure is given as shown in Fig. 7. The proposed HIF detection method are generally divided into 4 steps, which are as follows:

Step 1. Start: When the detection method started, waveforms of zero-sequence current will be recorded and updated by D-PMUs. Meanwhile, topology of the distribution network and locations of D-PMUs are also provided.

Step 2. Feature Extraction: The “three peaks” HIF features are extracted by the band-pass filter designed in Section II.A. By combining with the topology information, HIF feature gray-scale feature images and corresponding region maps are formed.

Step 3. Feature Enhancement: Through the LEGIO-RAM mentioned in Section III, attention map Γ is generated and the corresponding HIF feature image will be effectively enhanced.

Step 4. Detection & Confirmation: A trained YOLO v2 object detection model, introduced in Section IV.A, will provide the results of predicted bounding boxes. By comparing with the region maps, eligible regions are recognized as predicted regions. Through a final reasonableness check, the confirmed HIFs will be alarmed.

V. SIMULATION AND VERIFICATION

A. Simulation Setting

In this paper, we verified the proposed HIF detection method with three distribution networks in PSCAD/EMTDC and one

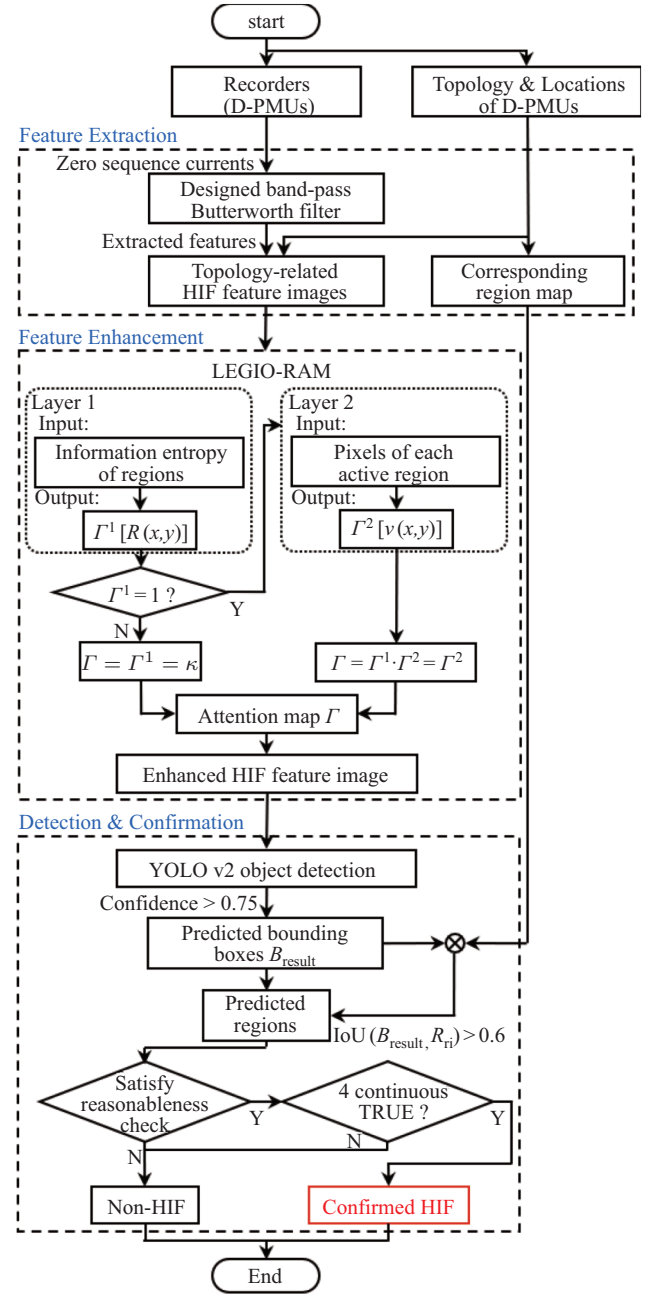


Fig. 7. Flowchart of the whole proposed HIF detection method.

actual experimental distribution network, numbered as 1–4. The three distribution networks are a 10 kV 20-node resonant ground distribution network (as shown in Fig. 3(a), No. 1), a 10 kV 17-node low-resistor-earthed neutral network (No. 2), and an IEEE 12.6 kV 33-node distribution network (No. 3). No. 4 is an actual experimental 10 kV distribution network used to test several HIFs in contact with different surfaces under three different grounding methods. Details about the practical experiment are described in Section V.C. The topologies of the No. 2 & 3 simulated distribution networks and the No.4 actual experimental distribution network with their corresponding region maps are shown in Fig. 8.

There are several different models to simulate HIFs. Based on the different theoretical bases, HIF models can primar-

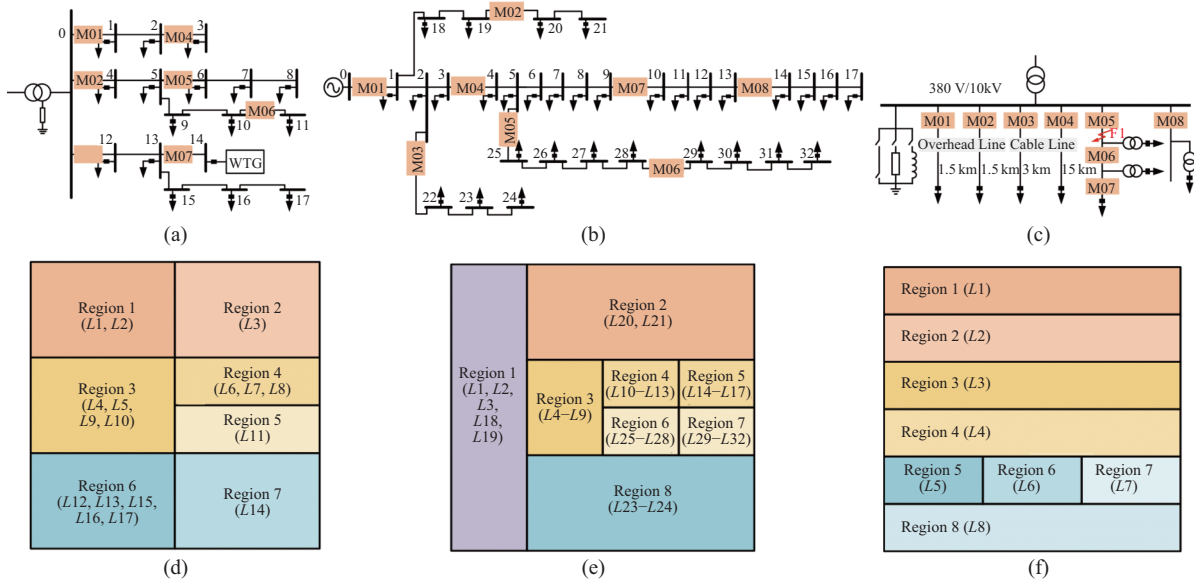


Fig. 8. Topologies and region maps of distribution networks. (a) A 10 kV 17-node low-resistor-earthed neutral network. (b) An IEEE 12.6 kV 33-node distribution network. (c) An actual experimental 10 kV distribution network. (d-f) Corresponding region maps.

ily be divided into accumulation theory-based HIF models (Cassie [29], Mayr [30], and other improved models [31]), solid dielectric electrical breakdown theory-based HIF models [32], and electronic element-based models. The anti-parallel DC-source HIF model is a typical electronic element-based model, which is easy to implement and has been widely applied in time domain simulations. By contrast, the first two types of HIF models simulate arc characteristics by introducing several differential equations, which have complicated construction processes. Meanwhile, this model can simulate almost all HIF characteristics and has similar harmonic levels as real reports [33]. As a result, the anti-parallel DC-source model is chosen as the HIF model in this paper, as shown in Fig. 9. Through adjusting different sets of parameters for the HIF models, we obtain 6 different types of HIFs based on comparing actual V-I characteristics of HIFs. Detailed introductions can be found in our previous research [21].

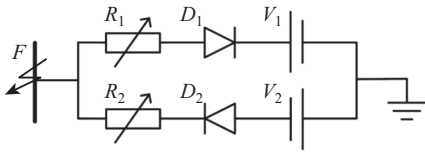


Fig. 9. Structure of anti-parallel DC-source HIF model.

For No. 1-3 distribution networks, we set 12 HIFs in each region, including 6 different types of HIFs in two different locations. No. 1 distribution network has 2 region maps corresponding to different D-PMU locations, as shown in Fig. 3(b) and (c). So, the simulation data is divided into No. 1_1 and No. 1_2, respectively. 10 different disturbances are set for each distribution network, including capacitors, DGs, and load switching. All the HIFs and disturbances occur at 0.6 s / 0.602 s / 0.605 s / 0.61 s to simulate the different initial phase angles (to avoid the effect of the transient process, all features

are extracted from 1 cycle after occurrence at the end). The step size of the time window is also set as 128 points, the same as the time window. Each scenario records 0.3 s from 0.1 s before HIF/disturbance occurrence. Based on the region numbers, each dataset of distribution networks can be divided as two datasets, which are No. x (o) and No. x (e) for the HIF occurrence region number is odd or even.

B. Verification Result in Simulation

Since a YOLO v2 network can train and detect any scale of images, the feature images extracted by different distribution networks can be used to train the detection model. In this paper, 4 YOLO v2 detection models are established by different input datasets, as shown in Table I.

TABLE I
INPUT DATASET AND AVERAGE PRECISION OF HIF DETECTION MODELS

Detection Model	Input Dataset	Average Precision (AP ₆₀)	
		In training datasets	In all simulation datasets
I	No. 1_1 (o)	100%	98.4%
II	No. 1_2 (o)	100%	87.3%
III	No. 1_2 (o) & No. 2 (o)	100%	93.5%
IV	No. 1_2 (o) & No. 3 (o)	99.1%	97.6%

Average Precision (AP) is introduced here to quantify the performance of the detection models. If the IoU(B_{pred} , B_{gt}) is higher than a threshold (in this paper, we set it as 0.6, which can be written as AP₆₀), the result is considered true positive classifications |TP|, otherwise it is a false positive |FP|. The amount of missed ground truth classifications is called |FN|. The AP is to evaluate the precision by the Precision-Recall curve as:

$$AP = \int_0^1 p(r)dr$$

$$p = \text{precision} = \frac{|TP|}{|TP| + |FP|}, r = \text{recall} = \frac{|TP|}{|TP| + |FN|} \quad (20)$$

The AP in training datasets and all simulation datasets are also shown in Table I.

From the results of AP_{60} , we can see that the HIF object detection model is easy to train and achieve a high accuracy rate, since the proposed LEGIO-RAM enhances features and more easily makes the object detection network focus on key regions. As a result, AP scores primarily depend on the number of training feature images. The YOLO v2 model I can reach 0.984 AP through training by feature images of No. 1_1 (o). By comparison, the detection model I', which is trained by the feature images No. 1_1 (o) without adoption of LEGIO-RAM, only has a 0.731 AP_{60} score. The Precision-Recall curves of these two models are given in Fig. 10.

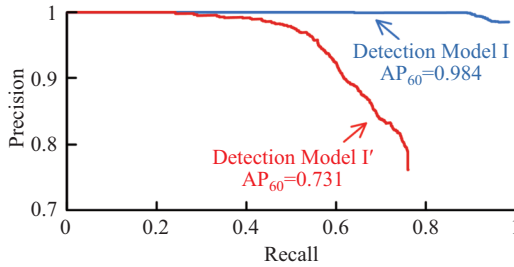


Fig. 10. Precision-Recall curve of detection model I with and without adoption of LEGIO-RAM.

The proposed method in this paper adopts steady-state characteristics, which is not affected by the fault initial phase angles. Meanwhile, we verified the proposed method under errors caused by measurement noises in distribution networks. The measurement noises are generated by adding different signal-to-noise ratio (SNR) Gaussian white noises to the original data. Table II shows the average precisions of detection model I under different SNR noises. According to the verification results, the proposed method has good performance in robustness for higher than 20 dB measurement noises. It is because of the fact that the proposed method adopts a band-pass filter to extract the features under a specific frequency band. As a result, measurement noises with different frequencies will be effectively eliminated.

TABLE II
AVERAGE PRECISION OF DETECTION MODEL I UNDER DIFFERENT SNR MEASUREMENT NOISES

SNR of Noise	Average Precision (AP_{60}) in all simulation datasets
50 dB	98.5%
40 dB	97.8%
30 dB	98.4%
20 dB	98.2%

For disturbances caused by operations, the proposed method also has good robustness. We simulated capacitors /DGs /load switching in different locations in all three distribution networks. Unbalanced device switching can cause transient processes, which may lead to fluctuations of zero-sequence

current. But these fluctuations are presented as transient processes, which last for a short period (generally shorter than 1 cycle) and are not primarily consisting of 3rd harmonic. According to Section IV, HIF detection should satisfy two conditions: the object detection result is TRUE and higher than 4 continuous TRUE results. Through filtering by these two requirements, all the disturbances cannot be misjudged as HIFs.

C. Verification Result in Practical Experimental Distribution Network

In a 10 kV 50 Hz actual experimental distribution network with the topology shown in Fig. 7(c), 15 artificial HIF experiments were performed and recorded to verify the proposed method. Positions of fault $F1$ and measurements M01-M08 (with sampling frequency of 6.4 kHz) are shown in the figure. The load currents range from 15 A~30 A (RMS). The distance between the fault point and the measuring point M05 is 80 m in electrical distance. HIFs are tested in different types of contact surfaces, including dry/damp soil, dry/damp cement, and asphalt concrete, under three neutral grounding modes (isolated neutral, resonant neutral, and low-resistor-earthed neutral). By verification, all these HIFs are correctly detected and located by the detection model I. Taking the dry cement-grounding HIF (a relatively serious condition that has extremely low fault current level and is under a severely noisy environment) as an example, waveforms of both ends of fault regions and the detection result of the proposed method are shown below.

Figure 11 indicates that the dry cement-grounding HIF has a zero-sequence fault current of lower than 1 A with serious noise. Through feature extraction by the designed Butterworth filter, the “three peaks” phenomenon distinguishes the measurements located upstream of the HIF from all measurements.

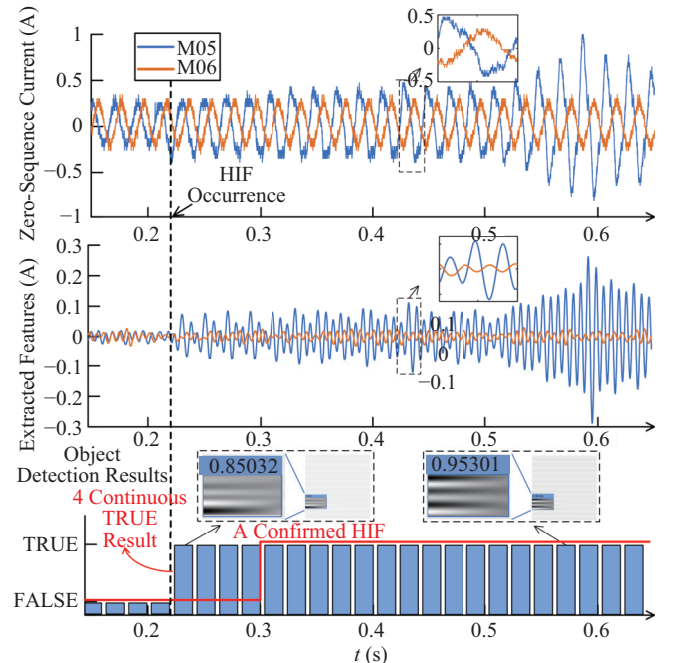


Fig. 11. HIF detection results of a real dry cement-grounding HIF.

The detection results show that the predicted bounding box of the first cycle after HIF occurrence has 0.85 confidence, which is higher than the threshold of 0.75. After receiving 4 continuous TRUE detection results, a HIF is confirmed by the proposed method. The $\text{IoU}(B_{\text{result}}, R_{r-5})$ of all results are larger than 0.9, and there is no other region with a larger than 0.6 IoU value. As a result, the determined HIF region is Region 5.

VI. CONCLUSION

In this paper, an object detection-based HIF detection method is proposed with the application of D-PMUs, which has good interpretability and generalization. Through analysis of HIFs, a Butterworth filter is designed for extracting the “zero-off” characteristics. Combining with topologies and locations of D-PMUs, this paper develops the region maps and corresponding feature gray-scale images to reflect the HIF features and locations. To further improve the feature images, LEGIO-RAM is proposed to highlight the key regions and enhance the feature information. At last, it was concluded that the combination of the trained YOLO v2 object detection network and region maps can quickly detect the HIFs and locate the regions at the same time. Through verification by three simulated distribution networks and one realistic distribution network, the proposed method can effectively achieve HIF detection and section location without the effect of fault types/locations/initial angles, measurement noises, and disturbances. The generalization ability of the proposed method shows that it has a good potential for practical applications.

The proposed method has a high requirement for accuracy and sampling rate of measurements. Otherwise, the features may have problems to be extracted. In addition, the 3rd harmonic component is the key characteristic of HIFs identified by this method. The 3rd harmonic continuously produced by elements, except the main transformer, may cause an incorrect alarm. The proposed method is designed for MV distribution networks. The application in LV distribution networks needs further studies concerning the effect of the complex harmonic environments. Another aspect to note is the choice of object detection algorithms. We had verified the performance with YOLO v2 and YOLO v3 in this method, and the detection results are almost the same. As a result, although we believe that YOLO v2 and v3 can handle the task in this method, we still choose the YOLO v2 here because YOLO v3 cannot show enough improvement and attraction. However, if the proposed method is expanded to other more complex tasks, such as abnormal events identification with more detailed features, the newer YOLO versions v3, v4 or v5 may have better performance than v2, which is considered as our future study.

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