Adaptive Event Location Technique via Time Difference of Event Arrival

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***Abstract*—This paper presents the phasor measurement unit (PMU) based event localization technique. In order to achieve the event localization in real-time manner, the proposed method is based on the measurement of the time required of the event propagation at each PMU. When an event propagates through the transmission network, there exists a time delay to arrive electrical buses in wide-area condition. As an initiated time of the event is unknown information in the practical power systems, time difference of arrival (TDoA) is used to estimate the event location instead of time of arrival. In this regard, the key point of the proposed localization utilizes the comparison of TDoA features that are composed of entire transmission lines to estimate the propagation path. As a result, the directions and time difference values in the shortest path are developed as features under the assumption of event location. Furthermore, a historical event-based network training method is proposed to substitute the system state estimation and calculation of propagation speed. Finally, the comparisons between calculated and measured TDoA features could estimate the event bus, and real-world test shows successful estimation results.**

***Index Terms*—Event location, dynamic event, PMU, synchrophasor, electromechanical wave, time difference of arrival (TDoA).**

I. Introduction

OWING to the increasing complexity and capacity of the modern power systems, preventing the system malfunctions from fault or event has become important task. In this regard, wide area monitoring system (WAMS) has been developed to prevent and mitigate the cascading malfunction from events. In addition, real-time localization techniques can tell where a disturbance has been initiated in the power systems and provide operators with a timely warning and predictive protection countermeasures to mitigate the effects of the disturbance [1]. Although the faults are detected through the status of local protective relay and breaker, mis-operating and location of the protection system has itself could be one of the causes of malfunctions such as wide-area blackout [2]. Under the support of the developed communication systems, WAMS has potential applications to prevent the mis-operating of protection systems in wide-area power system, and take an action to mitigate the propagation of the faults, and support quick repair and restoration of faulted transmission systems [3], [4].

Recently, phasor measurement unit (PMU) has become one of the key techniques in WAMS. It can significantly improve the performance of WAMS owing to the GPS-based time-synchronization and a higher sampling rate than traditional supervisory control and data acquisition (SCADA) systems [5], [6]. The development of PMUs and communication systems fully exploit the potential of capability to access these synchronized high sampling measurement values, enabling accurate and fast methods of event location, which has a potential in real-time monitoring [7]–[9].

With the widespread use of PMUs in transmission systems, there have been a number of studies to use the PMU as an event location indicator [10], [11]. The PMU-based approaches include the selection of the highest deviations in the nodal voltage and frequency signals [12], impedance estimation in the transmission line model [13]–[15], determining the current unbalance location using PMU and monitoring the corresponding fault index through the transmission line [16]–[18], and detecting event area using generator rotor angle monitoring [19]. Each approach is developed to provide the event location following their objective and target system condition. Thus, it is not easy to directly compare the performance including accuracy, resolution and computational time. In addition, guaranteeing the desirable PMUs is issue in real-world condition due to the bad data as well as unmonitored area around the event location [20].

In this work, we propose the method to develop the adaptive event location technique using time difference of wave arrival concept in practical power systems. When the event is initiated, caused disturbance signature is considered to be propagated through the transmission network. Several studies adopt the propagation model based analysis to estimate the event location [21], [22]. For examples, those studies include the analysis of the electromechanical wave to anticipate the event arrival time [23], anisotropy of the frequency propagation speed [24], sparse measurement of the electromechanical wave oscillation [25], [26], etc. In the model-based analysis, it is important to recognize the propagation path of the event and track the event location using the directions and the time required at transmission network. Although those studies show the high accuracy in wave velocity, there are challenges to be applied to practical power systems.

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The purpose of this research is to propose an data driven method to extract the event propagation information from PMUs and develop an event localization technique in practical condition. While time of event arrival (ToA) could be useful information in modeled systems, there exists an unpredictable error due to the systems condition as well as system modeling error. On the other hand, we propose an estimation method by comparing the features of direction and the time required to propagate at unit of transmission line instead of real value. Then, the estimation of event location is based on the optimization of directions between measured and anticipated values at entire transmission lines. In addition, a calibration of the propagation network using the historical event-based training is proposed instead of calculating wave velocity. Finally, this work provides the techniques for quantifying time difference of arrival (TDoA) in different signal shapes and achieves the data driven event location using calibration of relative values of the time required in transmission network.

This paper is organized as follows: Section II describes theoretical background of electromechanical wave and the method to measure the feature of TDoA using PMU signals. From the measured TDoA feature, Section III develops the algorithm for estimating event bus with a consideration of the shortest paths in power systems. In addition, Section IV describes the method for training the propagation network. Finally, proposed method is applied to real-world event cases and results are discussed at Section V.

II. Theoretical Background

A. Electromechanical Wave

The fundamental of the disturbance propagation through the wide-area could be analyzed using the wave propagation mechanism. When the event causes mismatch of electrical toque and mechanical toque, the disturbance is considered to be propagated through the transmission system as a form of wave. In this regard, concept of the electromechanical wave is considered to analytic method for disturbance propagation, which includes the power angle variance phenomena from electrical and mechanical toque mismatch. In the electromechanical wave phenomena, wave propagation depends on system parameters such as distributed inertia and transmission line characteristics. To analyze the affecting factors to wave propagation, two derived results about structural frame model and continuum model are introduced in this subsection.

In structural frame model, the impact scope of the generator inertia is proposed by introducing the inverse process of a lumped mass method. Then, for distributed generators and linearization of the generator motion equation, unbalance power relationship is obtained as follows [22]:

$$2H\omega_0 \frac{d^2\Delta\phi}{dt^2} = -\Delta P_e \tag{1}$$

where H is distributed moment of inertia, ω_0 is system frequency, $\Delta\phi$ is a power angle increment, and ΔP_e is the unbalanced power caused by the disturbance. In addition to the relationship in (1), the electric power output ΔP_e of the incremental generator location x_0 consists of power outputs in right and left sides of x_0, where ΔP_{e^+} and ΔP_{e^-} are electrical power outputs of two sides x_{0^+} and x_{0^-}, respectively. For the small value of $\Delta\phi$, it is known that the relationship between electric power outputs are as follows:

$$\Delta P_{e^+} = \frac{V^2 b}{\Delta x_0}\sin(\Delta\phi_{x_0} - \Delta\phi_{x_0^+}) \tag{2}$$

$$\Delta P_{e^-} = \frac{V^2 b}{\Delta x_0}\sin(\Delta\phi_{x_0} - \Delta\phi_{x_0^-}) \tag{3}$$

$$\Delta P_e = \Delta P_{e^+} + \Delta P_{e^-} \tag{4}$$

where b is susceptance of unit length transmission line, and V is voltage level. In the equation (2) and (3), $\sin(\Delta\phi_{x_0} - \Delta\phi_{x_0^+})$ could be simplified to $(\Delta\phi_{x_0} - \Delta\phi_{x_0^+})$, and could be expanded to terms of second order Taylor series. Then, (4) is replaced by the equation as follows:

$$\Delta P_e = -V^2 b \frac{\partial^2\phi}{\partial x^2} \tag{5}$$

where the ΔP_e is corresponding to the result in equation (1). From the combination of the ΔP_e representations in (1) and (5), it is possible to derive the electromechanical wave equation in the basic segment as follows:

$$2h\omega_0 \frac{\partial^2\Delta\phi(x,t)}{\partial t^2} = V^2 b \frac{\partial^2\Delta\phi(x,t)}{\partial x^2} \tag{6}$$

where x is the location in power systems, h is distributed inertia in unit length, and the wave equation is represented by the formula of the angle disturbance propagation. Detailed derivation about the electromechanical wave in the structural frame model is described in [22].

On the other hand, in the continuum modeling, which describes the power systems with spatially distributed parameters, any point in power system is represented by the incremental system. The continuum modeling allows representation of transmission lines with different impedances, shunt reactances, generators and loads. The equation (7) is a summary of continuum formulation with Taylor series expansion about location x as follows [25]:

$$P = \frac{R}{|Z|^2}\left(\frac{\partial\delta(x)}{\partial x}\right)^2 \Delta x - \frac{X}{|Z|^2}\frac{\partial\delta^2(x)}{\partial x^2}\Delta x \tag{7}$$

where, the net real power transfer at point x is P, $\delta(x)$ represents the phase angle of voltages at x, and R, X, Z represent resistance, reactance, impedance of the branch, respectively. Then, by applying the known continuum equivalent of the load flow equation of the power systems and the internal generator phase angle dynamics modeling, we obtain as follows [25]:

$$m(x)\frac{\partial^2\phi(x,t)}{\delta t^2} - d(x)\frac{\partial\phi(x,t)}{\delta t} = P_m(x) - \frac{P_G(x)}{\Delta x} \tag{8}$$

where $m(x)$ and $d(x)$ are generator inertia and damping factor, respectively, P_m is mechanical power at x, and P_G is transferred real power. Equation (8) is known as continuum equivalent of swing equations of the power systems. The derivation of entire process of wave equation in continuum model has large amount to discuss in this paper, where detailed derivation about wave equation could be founded in [25]–[27].

From the derived wave equations in (6) and (8), the speed of electromechanical wave depends on the system parameters. As both equation (6) and (8) are second order hyperbolic wave equation, the coefficient of the Laplacian is the square of the speed of the wave. The studies about discussed two models derive the speed of wave as follows [22], [25], [27]:

$$v_{struc} = V\sqrt{\frac{b}{2h\omega_0}}, \quad v_{con} = \sqrt{\frac{\omega_0 \cdot \sin\theta}{2h|z|}} \tag{9}$$

where the v_{struc} is the speed of the wave in structural frame model and v_{con} is the speed of the wave in continuum model, respectively. Note that v_{struc} and v_{con} have different approaches for the speeds of wave due to the different modeling structures of power systems, while both approaches have common system parameters in their representations of the wave speed. The primary parameters are unit length distributed inertia h, system frequency ω_0, impedance components z and θ, which require estimation process in the practical systems. However, this estimation process cannot be performed in real time, and there exist additional unpredictable propagation parts using electromechanical wave such as transformers between different level transmission systems. In other words, it is not an easy task to calculate the exact wave propagation due to the gap between the model and practical systems. Thus, there might be error between the calculated and measured speeds, which will result in a misunderstanding of estimated event location. This work proposes the substitutable method which performs the learning and localization process using the feature matrices instead of estimation of system parameters. The proposed method analyzed the ratio of the linearized slope using only the PMU measurement signals as the characteristic corresponding to the ratio of the propagation time.

B. PMU-Based TDoA Measurement

In advance of developing event location algorithm, it is needed to develop the features of TDoA measurement. There are several technical issues to measure time difference in the practical power systems. As the speed of electromechanical wave is much lower than that of electromagnetic wave, it is possible to measure the time difference of wave arrival using not extremely high sampling measurement. PMU is efficient solution for measurement, because only PMU provides the time-synchronized phasor data with high sampling rate in wide-area power systems. However, in spite of the higher sampling rate than that of SCADA systems, TDoA is not clearly distinguished within sample unit with a consideration of sampling rate of PMU (30-60 Hz). According to the technical reports, reported range of electromechanical wave speed in real-world systems is 100 mi/sec. to 1000 mi/sec. [19]. As a result, PMU-based studies adopt the measurement of triggering time of threshold value at frequency, in which the power angle wave propagation is represented as variation of frequency signal [24].

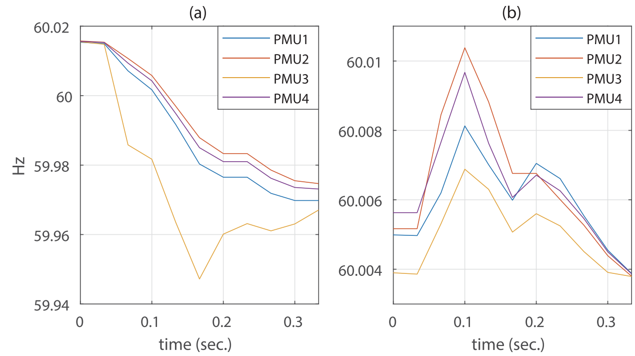

Fig. 1. Frequency signals of 2 event cases from 4 PMUs (PMU 1-4) at (a) generator trip event, (b) substation failure.

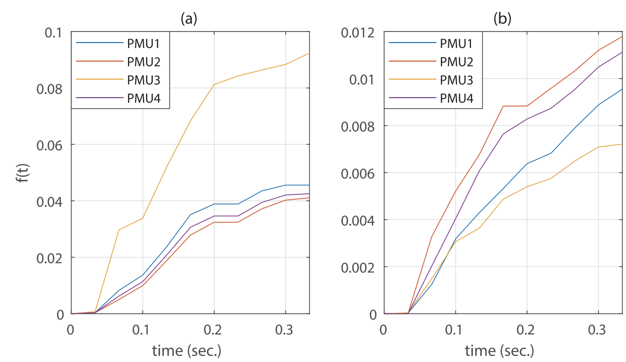

Fig. 2. Accumulated value $f(t)$ of the absolute ROCOF signals in Fig. 1.

To measure the direction and the required time of event propagation in frequency signal, front wave part of frequency signal is considered to arrival of event. While ToA of event cannot be measured because of unknown information of event occurrence time, time difference can be obtained between PMUs. However, when we consider practical PMU signals such as signals in Fig. 1, in which event cases in Fig. 1-(a), (b) are generator trip event and substation failure cases, it is hard to determine the constant threshold value due to the different shape of event signal. Moreover, reaching time to the threshold value depends on the event type and scale. Instead of measuring the arrival time, PMUs are directly compared with each other at front wave part.

In this work, ROCOF (rate of change of frequency) signal is considered to compare the PMU signals. Event signals in Fig. 1 are formulated to problem of measuring triggering time in absolute values of ROCOF and estimate the ratio between the required time required in each path. Although the ROCOF signal also has different fluctuations, the accumulated value of the absolute ROCOF signal can be analyzed to a monotonically increasing variable as shown in Fig. 2. Representation of accumulated value of absolute ROCOF signal is as follows:

$$f(t;k) = \sum_{n=0}^{t/\Delta t} |\text{ROCOF}(n\Delta t)|, \; t = k\Delta t \tag{10}$$

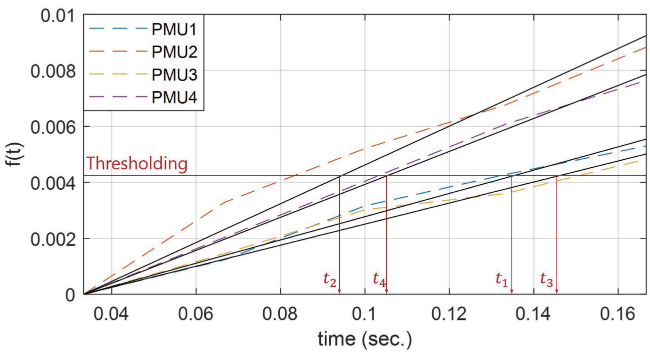

Fig. 3. Linear approximation of ROCOF and ratios between the thresholds.

where t is time with positive integer k, Δt is sampling period of PMU, and discrete signal $f(t;k)$ is accumulated value of absolute ROCOF value represented in Fig. 2. Then, by linearization of the ROCOF signal using the linear least square solution, it is possible that the problem of measuring the threshold time ratios between PMUs are corresponding to obtain the slope differences of Fig. 2 without determining threshold value as shown in Fig. 3.

From the observation of Fig. 3, there is a relatively large error may be introduced between the original fluctuation and linearized slope. Nevertheless, the reason of extracting the TDoA features through linearization is that linearization process does not require the threshold setting by replacing the time differences with the differences between the slopes. Note that the initial value of signals in Fig. 2 and 3 is reset to zero value to intuitively show their slopes, in which initial value might be reset to fixed value for the convenience because it is independent of calculation of their slopes. The formulation to measure the linearized slope is as follows:

$$\alpha_i = \frac{\sum_{k=1}^{N_w} k\Delta t \cdot (f_i(t_0 + k\Delta t) - f_i(t_0))}{\sum_{k=1}^{N_w} (k\Delta t)^2} \tag{11}$$

where, $f_i(t;k)$ is the absolute values of ROCOF at time t of i-th PMU, α_i is slope of i-th PMU, t_0 is triggering time, and N_w is a window sample length of the front wave from triggering location. Although t_0 is not actual event occurrence time, it is possible to construct the difference of slopes as a formula of matrix by combining line values, in which the relationship between the slope and time difference ratios are considered as follows:

$$\alpha_{ij} = \alpha_i - \alpha_j = c \cdot (t_i - t_j) = c \cdot t_{ij} \tag{12}$$

where t_{ij} is the actual time difference by thresholding, c is a scale-related element between actual TDoA and normalized TDoA feature, and α_{ij} is the difference of slope of i, j-th PMUs. In this case, c is a scale-related element between the difference of slopes and time difference values. Since the proposed training and estimation process depends on the correlation analysis of the TDoA features, the influence from various c values is eliminated, and estimate of the c value is not required. Note that the proposed method uses combination of the relative values to construct the feature matrix instead of real time difference values, where the feature is available in case of the known network topology and detectable transient event condition. Finally, real-time monitoring recognizes the TDoA measurement from α_{ij} values of PMUs, in which combination of α_{ij} values are constructed as a TDoA feature.

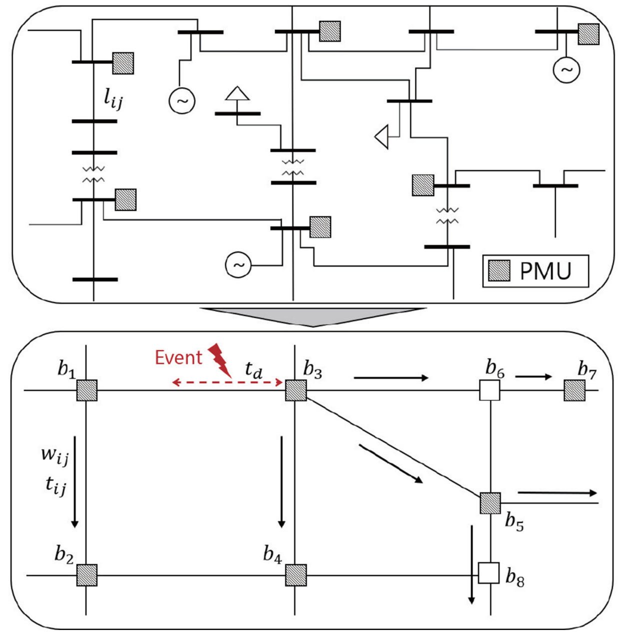

Fig. 4. Concept of event propagation using network analysis.

III. Event Location Technique

A. Network Topology Analysis

With a known topology of the power systems network and propagation time ratios between the PMUs, our task is to estimate the event location using measured TDoA features. The fundamental of event propagation is that TDoAs are the time required through the shortest path between PMUs. Although TDoAs could be defined at entire PMU connections, only TDoA values located in one of the shortest paths are actual TDoA information at transmission lines. In other words, measured TDoA values from the transmission line out of the shortest path does not represent the time required. To construct the meaningful TDoA features, the connections of electrical buses are represented to network matrix, in which the number of buses has a tradeoff between computational time and measurement reliability.

To clearly explain the meaningful TDoA values, part of typical power systems is depicted in Fig. 4, in which w_{ij} is the weight value of the time required and t_{ij} is measured time difference between bus b_i and b_j, respectively. In general power systems, PMUs have been installed to have efficient observability of buses using minimum number of PMUs [28]. Assuming the fixed PMU installation status in the targeted power system, the reduction process to construct the network matrix is as follows: 1) The connections between two PMUs with combinations of straight lines are replaced by one transmission line and the corresponding weight value, where unmonitored buses between the two PMUs are removed. 2) The branch bus is generated at the branch connections regardless of PMU measurements, where three or more PMUs are connected through branch bus. 3) If there is no two terminal PMUs in the line, corresponding measurement value of the line is obtained by dividing the slope differences of adjacent PMUs into ratio of weight values. 4) The normalized physical length of transmission line is used as initial weight value, and weight value is calibrated to reflect the ratio of required time through the training process. The different voltage level power systems are model as one network through the connection of transformers. When the event occurs in transmission systems as described in Fig. 4, PMUs recognize the event occurrence with time delay t_d, which is time to be propagated to nearest PMU to event location.

In this work, the notation $M(x,y,r)$ matrix is defined as the measured TDoA features of (12), and $W(x,y,r)$ matrix is composed of weight values w in network matrix, respectively, where x, y are connected buses and r is per unit length between bus x and y. The number of components of $M(x,y,r)$ and $W(x,y,r)$ matrices is same with the number of connections in reduced network matrix, and location (x,y,r) determines the compositions of zero components in $M(x,y,r)$ and $W(x,y,r)$ matrix. The components of the $M(x,y,r)$ and $W(x,y,r)$ matrix which are not included in the at least the one shortest paths from location (x,y,r) are replaced by the zero value. For example, if event location is correctly estimated in Fig. 4, measured TDoA $t_{12}, t_{34}, t_{35}, t_{37}, t_{67}$ are expected to have correct directions and ratio of actual time required to propagate between the transmission lines, while $t_{13}, t_{24}, t_{48}, t_{56}$ are not actual the time required because wave arrives the terminal buses through the different paths. Finally, when the actual event location is corresponding to estimated location, calculated TDoA features would be expected to be correlated with measured TDoA features as follows:

$$W(1,3,r) = [w_{12}, 0, 0, w_{34}, w_{35}, w_{36}, 0, 0, w_{58}, w_{67}] \quad (13)$$

$$M(1,3,r) = c \cdot [t_{12}, 0, 0, t_{34}, t_{35}, t_{36}, 0, 0, t_{58}, t_{67}] \quad (14)$$

where $W(x,y,r)$ and $M(x,y,r)$ are composed of values at entire transmission lines with an assumption of event location r between bus $x = 1$ and $y = 3$, in which zero values of $(t_{13}, t_{24}, t_{48}, t_{56})$ are not located in one of the shortest paths. Also, in case that simplified line is not monitored by two terminal PMUs such as t_{36}, t_{67}, TDoAs are determined by the weight ratio as follows:

$$t_{36} = \frac{w_{36}}{w_{36} + w_{67}} t_{37}, \quad t_{67} = \frac{w_{67}}{w_{36} + w_{67}} t_{37} \quad (15)$$

where bus b_3 and b_7 are located in one of the shortest paths. As a result, if the event location (x,y,r) is correctly estimated, the correlation between the following $W(x,y,r)$ matrix and $M(x,y,r)$ matrix is higher than other correlation values. Calculation of the shortest path is performed by the Dijkstra algorithm [29], and those processes are discussed as localization algorithm in next Section III-C.

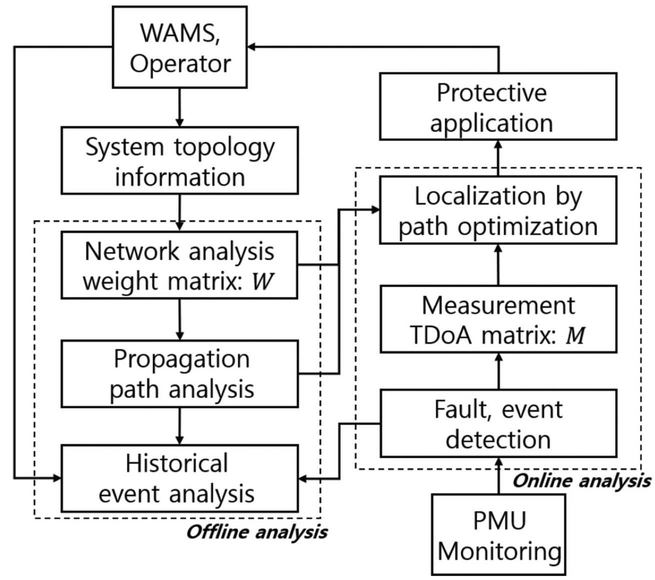

Fig. 5. Flowchart of event location based protection systems.

B. PMU-Based Event Monitoring

To estimate the event location in real-time manner, proposed event protection system is composed of online and offline analysis as illustrated in Fig. 5 flowchart. Based on the known network topology, entire shortest paths could be obtained under the assumption of event location, and calculated weight values are saved as data set in advance of real-time localization, which are constructed as weight matrix W. In addition, calibration of W matrix by network training is considered to improve the accuracy of location using historical event data, which is described as the training process in next Section IV. In spite of variance in network topology such as additional transmission line, trained ratio is still useful because it could be used as initial network. Finally, paths from each electrical bus are determined in offline condition with initial weight of the time required with applicable data including physical length, impedance, inertia and historical event data.

In advance of event localization, event signals should be detected by PMU-based event detection studies [30], [31]. In addition, bad data detection and management should be considered such as missing data, quantization error, etc. from misunderstanding of data. With an assumption that event detection has an ability to detect bad data in real-time manner, bad data input is considered to zero value in proposed event localization. Then, TDoA features are measured from front wave in frequency signals, which have the propagation directions and weight values. In this regard, features of calculated and measured TDoA are compared according to the assumption of the event location. If assumed event location is corresponding to the actual event location, TDoA features would have higher correlation value than other locations. Detailed optimization process to estimate the location is represented in next subsection. Finally, estimated event location is reported to system operator, which can be used to event protection system through prevention and mitigation

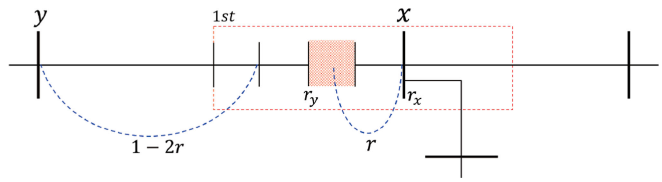

Fig. 6. Event localization in transmission line using binary search.

of event. During the real-time monitoring, it recognizes the additional event, and variations in network topology might be updated to calculate the new paths.

C. Event Location Technique

Event location is determined by similarity of corresponding two features, in which assumption of event location determines the both of calculated and measured TDoA features. For the similarity of TDoA features, corresponding two features are obtained from entire points as event location and correlation values are calculated to measure the similarity in different scale. However, it is hard to calculate the optimal point by iterative computation because the any point of system could be event location. In this work, the variable to represent the event in power systems is two buses x, y and the length of location r between the buses. Then, estimation of location is problem of optimization of the x, y, r values to maximize the value of correlation between corresponding two features as follows:

$$[x, y|r] = \underset{x,y|r}{\arg\max}[corr(W(x, y, r), M(x, y, r))]$$
$$= \underset{x,y|r}{\arg\max}\left[\frac{\sum_{i=1}^{N_L}(w_i - \overline{w})(m_i - \overline{m})}{\sqrt{\sum_{i=1}^{N_L}(w_i - \overline{w})^2 \sum_{i=1}^{N_L}(m_i - \overline{m})^2}}\right] \quad (16)$$

where W and M are weight and measurement TDoA matrix of N_L lines, respectively, which are composed of values at each transmission line, and $corr$ is correlation value between the W and M. The iterative optimization process requires heavy computation, in which the process computes the 3 variables at the same time. However, in real time process, lower computational time is required to achieve the localization in objective time. Thus, we propose the sequential optimization method to reduce the computation with a consideration of power system structure, in which the nearest two buses x and y to event location are determined in advance of computing the distance ratio r between the bus x and y. In other words, optimization process to obtain the variables (x, y, r) could be formulated to restrict the electrical buses x and y, and region between the buses by simple comparison of correlation values.

In case of propagation through the transmission line, nearest bus to the event location is expected to have higher $corr$ function value than other buses. Fig. 6 is represented to explain the searching process. If bus x has the highest correlation value among the other buses, 1st event area is reduced to area composed of the half lines with connected buses. The formulation for obtaining x is shown as follows:

$$x = \underset{x \in bus}{\arg\max}[corr(W(x, x, 0), M(x, x, 0))] \quad (17)$$

where x is one of the buses in network matrix. In the same manner with determining x, y is determined by comparing the $corr$ function values among the connected buses with bus x. Bus y is expected to have higher $corr$ than other buses connected with bus x. Equation for determining bus y is also based on configuration of W and M matrices assuming event location to bus y as follows:

$$y = \underset{y \in bus_x}{\arg\max}[corr(W(y, y, 0), M(y, y, 0))] \quad (18)$$

where the notation $y \in bus_x$ is used to represent that bus y is one of the connected buses with bus x. In this stage, it is clear that bus y provides the higher $corr$ value than assuming other bus_x to event location. Finally, location between the bus x and y is specified by reducing the transmission line length using binary searching. The key-idea of the binary searching is to restrict the section of event location by dividing the interval into half section in each step by comparing the two correlation values in opposite directions. The representation of location r is updated at every binary searching step, and each n-th iteration is performed as follows:

$$\begin{aligned} r_0 &= \frac{1}{4}, r_x = r_{n-1} + \frac{1}{2^{n+1}}, r_y = r_{n-1} - \frac{1}{2^{n+1}} \\ r' &= \underset{r'=r_x,r_y}{\arg\max}[corr(W(x, y, r'), M(x, y, r'))] \\ D(n) &= \begin{cases} +1, \text{if} & r' = r_x \\ -1, \text{else} & r' = r_y \end{cases} \\ r_n &= r_0 + \sum_{n=1}^{N_b} \frac{D(n)}{2^{n+2}} \end{aligned} \quad (19)$$

where searching next step r_n from r_{n-1} corresponds to comparing the $corr$ values of two points r_x and r_y, and proceeding to higher direction by a half distance of the previous step. The reference location for the first binary searching is r_0 length from bus x considering the $1st$ event area in Fig. 6, and $W(x, y, r_{x,y})$ matrices are obtained by computation of shortest paths with reduced $1 - 2r_{x,y}$ weight of event line. In other words, r' is determined to r_x or r_y in each iteration, and $D(n)$ determines the proceeding direction according to r' value. If the event is located at r in case of $r' = r_y$ as shown in Fig. 6, system recognizes the event line as $1 - 2r$ p.u. weight because there exists a time delay of event identification at the nearest bus x. N_b is the number of binary searching steps which can be determined by operators considering the required spatial resolution and computational time by setting the r value.

IV. Network Training Method

As described in Section II, calculation of the electromechanical wave propagation is based on the state estimation including system inertia, system frequency, and transmission

Algorithm 1: Network Training Algorithm.

```
Input: weight matrix: W
Input: measurement matrix: M
while convergence do
    while (#events)×(#lines) do
        Compute: shortest paths
        Compute: fixed step size α
        if improve directions then
            weight matrix update: W' = W + αW
        end if
    end while
end while
while convergence do
    while (#events)×(#lines) do
        S.T.: fixed direction
        Compute: shortest paths
        Compute: fixed step size β, β < α
        if improve weights then
            weight matrix update: W' = W + βW
        end if
    end while
end while
```

line characteristics in the analytic models. On the other hand, based on the assumption that target system has historical event data from PMUs, it is possible to compare the propagation paths of calculation and measurement, and calibrate the weights of network. Also, if historical event data has enough event cases from various event locations, it is possible to substitute the system state estimation as well as calibrate the physical length using the network training. Moreover, it is possible to estimate the event location using only event data and trained network.

For the network training, gradient descent algorithm is generally used such as stochastic gradient descent in neural network [32]. However, optimization function in (16) is highly discontinuous and nonlinear function because weight calibration could change the paths and compositions of W matrix, which causes an error in $corr$ value in each step. In this regard, fixed step size based decent algorithm could be an efficient method to calibrate the weights.

Algorithm 1 shows the process of the network training using the historical event data, which is composed of iterations depend on the number of event cases and lines to calibrate the values in network matrix. In the Algorithm 1, $(\#events)$ is the number of training event cases and $(\#lines)$ is the number of entire lines in reduced network matrix. The proposed training process is corresponding to calibration of weight value w to improve the correlation value between the $M(x, y, r)$ and $W(x, y, r)$ at each iterative step. Note that the initial $W(x, y, r)$ matrix is generated by normalized physical lengths of transmission line and is used to initial input value of proposed Algorithm 1, where w are updated to network matrix after iterative calibrations. For the fixed step change of each line, values of weight matrix are calibrated to match the directions at each line with known event location, and detailed weight value optimization is considered within the fixed directions. The size of detail optimization step β is designed to have smaller value than that of path optimization α with numerical test. Determination of fix step size is related to the length error rate, which is considered to have range 0-0.05. Finally, the $(\#events) \times (\#lines)$ iterations are performed until the line convergence at each computation step.

If the large number of wrong paths are selected in initial training process, it might not guarantee the correct solution owing to the large number of meaningless paths. Thus, the initial correlation values between the $W(x, y, r)$ and the $M(x, y, r)$ matrices are adopted as variable to determine the suitable initial training set before applying the training algorithm. In case that network topology is changed according to development of power systems, this training result could be used to initial weight matrix for training or test after topology change. In condition that variations from daily operation are related to the overall inertia change rather than affecting the inertia variation in individual line, it is reasonable to assume that the effect of variation in system inertia is reflected in training process, because the effect of overall variations can be eliminated by the correlation analysis in the proposed algorithm. Network matrix could continuously reflect the structural change of network topology as well as trained weight values, where new line is updated by the normalized physical length of the transmission line.

V. Results in Real-World System

To test the proposed method in practical power systems, one of the electrical grids in southwestern part of the United States is targeted, where 30 Hz sampling rate PMUs are installed to monitor the transmission system. As a result of network analysis, the target system is simplified to network composed of 64 buses, 112 transmission lines, and 9 transformers between 345 kV and 138 kV transmission systems with 45 PMU buses. PMUs measurement data includes the voltage and frequency signals at buses of 345 kV and 138 kV transmission systems from 01/01/2013 to 04/30/2014, and we assume that network has fixed topology during that period. Also, detectable historical event cases in 345–138 kV level transmission systems are 46 cases with known event location. The 46 event cases are composed of location data in 28 different event sections (26 cases of 345 kV level, 20 cases of 138 kV level), in which the disturbances are caused by variety events such as generation losses, switching operations, protection system failures, and other unknown causes.

To achieve the PMU-based TDoA feature measurement in the target system, 8 cycles (4 samples in 30 Hz PMU) window size is used at front wave part of PMU frequency signals which is initiated within 0.2 sec. after event. As one of example of the TDoA features, Fig. 7 describes the TDoA values with actual event location for calculated values in Fig. 7-(a) and measured values in Fig. 7-(b), respectively, obtained from actual event location. Zero values in several components mean that the corresponding line is not located in at least one of the shortest paths. From the observation of Fig. 7, one can confirm that corresponding two features show high similarity, which indicates the reasonable result of event location estimation. In the same manner with Fig. 7, Fig. 8 describes another two features corresponding to

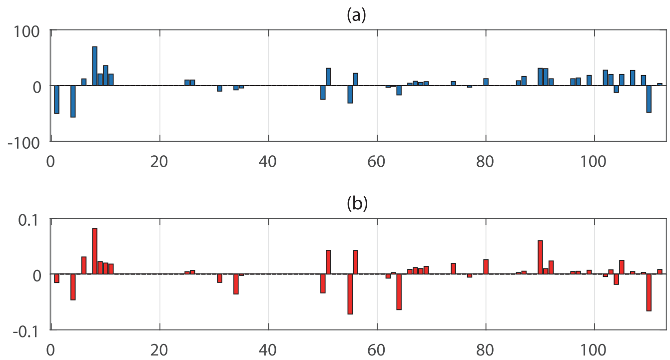

Fig. 7. Corresponding two features from correct assumption of event location (a) weights with direction, (b) measured TDoAs.

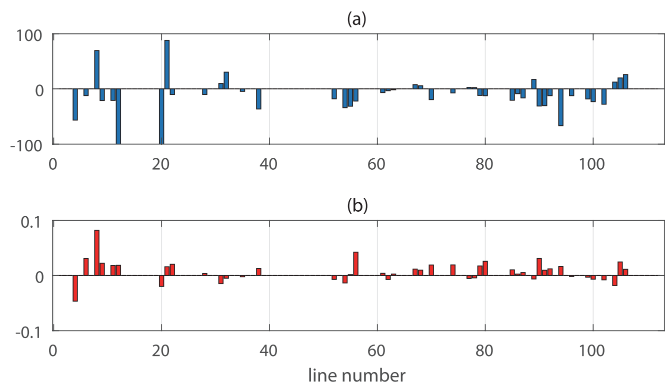

Fig. 8. Corresponding features from incorrect assumption of event location (a) weights with direction, (b) measured TDoAs.

far location from event, which represents the low correlation between calculated Fig. 8-(a) and measured Fig. 8-(b). The tests through the Fig. 7 and Fig. 8 are obtained with initial network matrix without estimation of system states.

For the training of network in the target systems, 10 event cases are used to training, in which *corr* value of corresponding known event location is higher than 0.7. Then, 10 cases are used for cross validation of remained event cases, in which results of two times test for 36 event cases are represented as average value of error length with event location. One of the examples of TDoA features using trained network are described in Fig. 9, which is trained version of event features in Fig. 7. From the observation, it is found that components of zero values are changed because the shortest paths are calibrated by training, and has a higher correlation owing to the training process.

Finally, the stochastic results of training test are described in Fig. 10 and Table I. The real-world event data provides the event location as a bus or transmission line section between two buses instead of exact location. Thus, test is conducted for restricted the event area with zero iteration of r. In the Fig. 10, in which the correct receiving rate are represented according to acceptable error length, x-axis represent the physical transmission line length of error and approximately 330 km is possible maximum error length in the target system. The correct receiving rate shows the improved high performance at training test. In the Fig. 10,

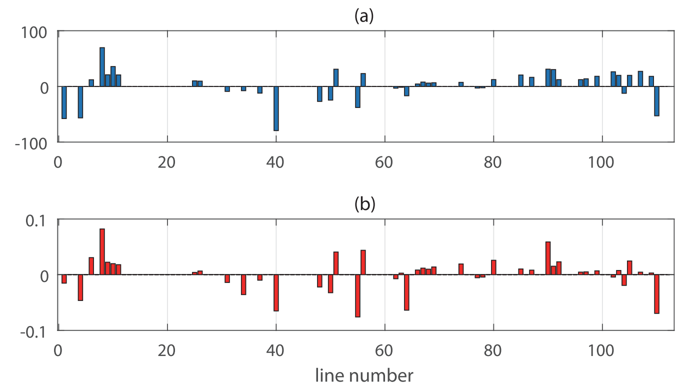

Fig. 9. Corresponding assumption with Fig. 7 in trained network (a) weights with direction, (b) measured TDoAs.

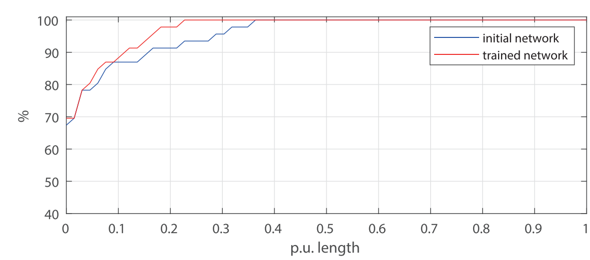

Fig. 10. Correct receiving rate of event location technique using initial and trained network (1 p.u. length = 330 km).

TABLE I
NETWORK COMPOSITION AND RESULTS IN TARGET SYSTEM

Line lengths (#112)	Initial test	Trained test
max.: 159.3 km	avg.: 14.47 km	avg.: 10.09 km
avg.: 30.1 km	max.: 120.6 km	max.: 77.7 km
var.: 894.7	var.: 905.1	var.: 375.2

70% of events are located in estimated section (67.4% of initial test) and 90% of events are located within 0.112 p.u. of maximum error length (0.157 p.u. of initial test) with actual event location. The statistical indexes of error rates are represented in Table I using the average, maximum, and variance values. It is not an easy task to apply the traditional method to practical system. Because events have various fluctuations which are unable to acquire the accurate time information under limited sampling of PMU, the system parameter estimation in real-time manner is a challenging task for the practical system application.

The performance of event location technique in real-world system is concluded in Table I. With a consideration that the average length of 112 transmission lines in 345-138 kV is 30.1 km, the average error length 10.09 km means that results are expected to be located within the event section and their connected transmission line because average error length is 33.5 % of average line length. The computational time for estimating the event bus x is 0.089 sec. using MATLAB in WIN 10, i7-7700 CPU, 8 GB RAM, and TDoA measurements are based on analyzing 4 samples of measurements which corresponds to the time within 0.13 sec. If the time to arrive at control decision after event localization is assumed within 0.2 sec., control could be initiated within 0.8 sec. after the disturbance is first detected. This amount of decision time satisfies the time delay between an event and control in earlier studies [8]. From those results, with a development of communication systems in smart grid, development of real-time event location and protection system is expected. In practical systems condition, developments of data management including bad data management, topology information, higher rate sampling measurement of PMU have an ability to improve the location accuracy in Fig. 10 and Table I. Also, correct and detailed information of event location in test measurement set is expected to improve the training results.

VI. Conclusion

This paper presents the real-time event location method using PMU measurement. For the application in the practical power systems, proposed localization algorithm is designed to only use the time difference features and network matrix trained by historical event data. Based on the electromechanical wave analysis, it is reasonable to extract the features of TDoA of each event case from the front wave part of the frequency signals. Then, the key-point of event location technique is formulated as simplified optimization problem of comparing the correlation values between calculated and measured TDoA features to achieve the fast and efficient estimation in real-time manner. Also, the proposed training method includes the calibration of propagation network matrix using the historical event data without a system state estimation. One of the benefits of the proposed method is development of data driven approach for practical power system instead of model-based approach, where the proposed algorithm can estimate the event location with the relative TDoA feature without the accurate time information and the process of estimating system parameters. Finally, the proposed algorithm is applied to the real-world test system and their 46 event cases, in which the proposed method shows high accuracy estimation results. In future work, we will investigate the real-time applications of the event location techniques including the event classification, analysis of hidden failure and corresponding protection schemes.

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