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Distributed Parameter Estimation for Mobile Wireless Sensor Network Based on Cloud Computing in Battlefield Surveillance System

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ABSTRACT The construction of a battlefield surveillance system is very important for monitoring the attack of enemy aircrafts and missiles, which integrates various sensors and mobile devices. Then, multiple battlefield surveillance systems can be connected together to form a battlefield surveillance network. The mobile nodes can be deployed in a certain region to monitor enemy aircrafts and missiles. Thus, some important issues have to be solved efficiently, including the cooperation across the administrative domains of a cloud network, the direction-of-arrival (DOA), and a polarization estimation algorithm for a mobile wireless sensor network (MWSN). In this paper, the architecture of a battlefield surveillance system is constructed based on mobile cloud computing and 5G link. The root multiple signal classification (Root-MUSIC)-like algorithm is proposed for estimating the 1-D DOA and a polarization parameter with a uniform linear array. The Root-MUSIC algorithm is replaced by the Fourier transform, the former algorithm that can be extended to an arbitrary topology structure of a MWSN. Then, the proposed algorithm is extended to the 2-D DOA and a polarization estimation in further. Based on the deployment of different MWSNs, the estimation results of DOA and polarization parameters are fused in order to improve the estimation performance. Finally, the parameter information (DOA and polarization parameter) of enemy aircrafts and missiles can be achieved. The computer simulation verifies the effectiveness of the proposed algorithm. The proposed algorithm ensures the parameter estimation accuracy with a low computational complexity.

INDEX TERMS Mobile wireless sensor network (MWSN), mobile cloud computing (MCC), direction-of-arrival (DOA) and polarization estimation, battlefield surveillance system.

I. INTRODUCTION

In recent years, cloud computing is continuing to have an important impact on communication networks, which is gradually becoming a promising technology. Mobile devices such as smartphone and tablet PC are increasingly becoming an essential part of human life as the most effective and convenient communication tools not bounded by time and place [1]. The mobile cloud computing (MCC) [2] is an especial part of cloud computing, which is suitable for computing on mobile devices. The massive computing, storage, and software services can be executed flexibly using much lower energy consumption in a scalable and virtualized manner [3]. Based on MCC, many applications with large computational complexity can be executed in the mobile devices.

The cloud networking is a new concept, which integrates different virtual sources from across administrative domains. The characteristic of cloud networking should be adaptive, reliable, scalable and autonomous.

In modern war, the weapons and equipments are more and more advanced, the early detection and tracking for the enemy advanced weapons such as aircrafts and missiles become a very important problem to deal with. Battlefield surveillance system integrates various sensors (including infrared and radio frequency sensor, etc) and mobile devices. The function of this system is to monitor and track enemy targets and to provide early warning of enemy targets. Detection and tracking of moving objects has been identified as a well-suited application, which would benefit from the use of mobile wireless sensor network (MWSN) [4]. Thus, we aim to construct a battlefield surveillance system exploiting the advantage of cloud networking. The first problem is the integration among multiple battlefield surveillance systems based on cloud networking. The second problem is the parameter estimation (it may contains the direction and polarization information. The direction information can be used to monitor the enemy targets, and the polarization information can be used to evaluate the type and model of the enemy targets.) of enemy aircrafts and missiles based on MWSN.

A. RELATED WORK

The cloud networking provides more powerful ability to analyse and process data than single cloud. An architecture that supports seamless virtual infrastructures deployed on-demand across multiple providers, including data centre and network operators was described. Issues related to inter-provider service provision, such as management delegation and cross-domain connection set up in the presence of limited information disclosure between parties have been addressed [5]. The common control channel problem in CogMesh was analyzed and feasible solutions were proposed. Based on control clouds, a cluster based network formation scheme was employed to further consolidate the spectrum management [6]. Technologies and protocols for cloud networking were discussed, which reviewed their applicability in addressing the networking needs of large-scale multi-tenant data centers. The cloud networking was reviewed briefly, and the new network architecture for future network was proposed [7].

MWSN has attracted much attention and has been used in many applications such as military target tracking and surveillance, animal state estimating and actuating, hazardous environment exploration and seismic sensing [8], which is composed of a large number of sensor nodes deployed either inside the phenomenon or very close to it [9]. The traditional nodes of wireless sensor network (WSN) are static, which does not have the mobility. If the nodes are deployed in the region that people can not reach easily (This condition always happens in the deployment of sensor nodes.), the positions of sensor nodes cannot be changed anymore. The optimal positions of sensor nodes are difficult to deploy based on the static nodes. However, the nodes of MWSN can move to anywhere in theory, the optimal positions can be detected in a stepwise way [4]. The integration of MWSN and MCC [10], [11] is expected to facilitate the development of data-driven surveillance and targeting systems in cost-effective and scalable way [12]. The advantage of mobile nodes is improving the coverage of sensor network and maneuvering to connect the lost or weak communication chains, etc.

The DOA and polarization parameters detected by the MWSN convey very important information about enemy targets, which have to be estimated accurately. Since the battery capacity of mobile node is limited, thus the search free methods which have a very low computational complexity are the best choices. The root multiple signal classification (Root-MUSIC) algorithm and spatial interpolation have been proposed for uniform linear array (ULA) [13]. In order to reduce computational complexity, the multiple dimensional searching is replaced by polynomial rooting. This method has been extended to non-uniform array based on spatial interpolation. However, this method is only suitable for 1D angle estimation. Based on this method, an L-shape array method has been proposed, the 2D DOA and polarization estimations have been achieved [14]. However, the parameter pairing is needed. The methods proposed in [15] and [16] can obtain 2D DOA and polarization estimations accurately and rapidly based on (estimate parameter via rotational invariance technique) ESPRIT algorithm with uniform rectangular array (URA). Then this method has been extended to arbitrary array configurations [17]. However, the direction and polarization of the sensor nodes have to be identical. Based on the manifold separation technique (MST) [18], the 2D root DOA and polarization estimation algorithm has been proposed with arbitrary array configurations and element directions [19]. However, the main problem of this method is to solve the high order dual nonlinear equations, which has a large computational complexity.

B. CONTRIBUTION

Three contributions are made in this paper. First, we construct the architecture of single battlefield surveillance system based on MCC and 5G-link as shown in Fig. 1. The MWSN is used for locating the position of enemy target. Second, we integrate multiple battlefield surveillance systems based on cloud networking and distributed control. Third, in order to solve the essence problem of this system, the parameter estimation of enemy target has to be done. a 1D DOA and polarization parameter estimation algorithm with uniform linear array (ULA) is proposed. Based on Fourier transform, this method is extended to arbitrary topology structure. Finally, we extend this method to 2D DOA and polarization parameter estimation.

The remainder of this paper is organized as follows. In section II, the system architecture for battlefield

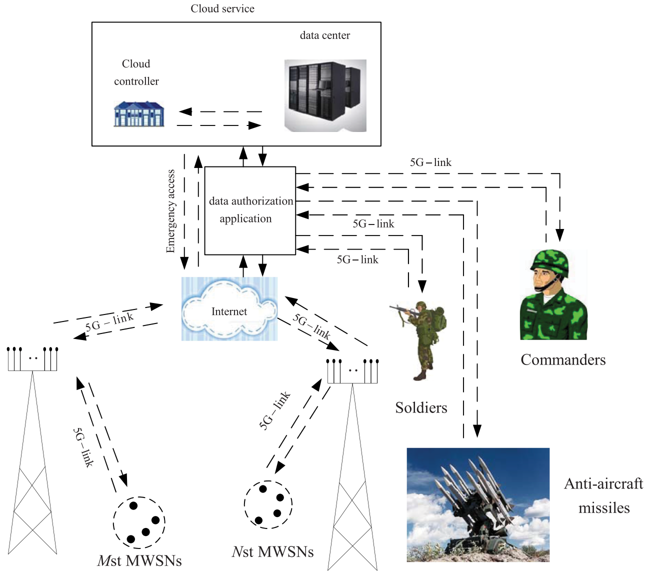

FIGURE 1. **The construction of single battlefield surveillance system.**

surveillance system is constructed. In section III, dynamic spectrum access (DSA) technique of cognitive wireless network (CWN) is introduced. In section IV, three distributed DOA and polarization parameter estimation algorithms are proposed. In section V, the simulation results are illustrated. Finally, in section VI, the conclusions are drawn.

II. SYSTEM ARCHITECTURE

A. SYSTEM CONSTRUCTION OF SINGLE BATTLEFIELD SURVEILLANCE SYSTEM

The construction of single battlefield surveillance system is shown in Fig. 1. The MWSN can be wirelessly connected to the Base Station (BS) through 5G-link. In the general case, the network between MWSN in the mountainside and the BS in the military base is sparse or even disjoint. Thus some mobile nodes can be deployed to connect lost or weak communication pathways. These mobile nodes can be called relaying nodes, which are equipped with large capacity batteries. Because they must forward more data messages than static nodes and the forward distance of mobile node is longer than that of static node. If not, these relaying nodes will die sooner. In addition, mobile BS equipped with large capacity battery can be also deployed in the sparse or disjoint region, which has powerful ability to process and forward data. The monitoring data can be routed to the data center for detailed evaluation. Similarly, the program can be executed in the cloud. Any abnormalities in the physiological measurement can be identified automatically based on intelligent early warning system (IEWS). When enemy aircrafts and missiles are coming, alerts or warnings can be sent to commanders and the military control center. The data transmission is almost through wireless way. Thus 5G network solutions can give possibilities of entirely new way for battlefield surveillance. Based on the advanced technique in 5G, the transmission rate will be improved dramatically as well as the capacity of channel. The real-time battlefield surveillance will be achieved in the future. BSs of massive multiple input multiple output (MIMO) system can be wirelessly connected to the Internet using 5G-link.

In the battlefield surveillance system, the most prominent surveillance objects are enemy aircrafts and missiles. Thus mobile nodes can be thrown down by aircraft in the deployment regions, which are far away from the military base. In order to monitor enemy air targets, deployment regions of MWSNs are vitally important to protect the military base. To the best of our knowledge, the mountainside facing the direction of enemy attack is an excellent place to deploy mobile nodes, as shown in Fig. 2. When enemy aircrafts and missiles are coming, sensor nodes can detect the electromagnetic wave sent by enemy objects. Acoustical and infrared signals can be detected by acoustical and infrared sensors, respectively. In addition, the noise level is very high because enemy aircrafts and missiles travel at supersonic speed. The friction of atmosphere against the surface of enemy aircrafts and missiles engenders high temperature at contact surface. The high temperature area can be detected by infrared sensors. These parameters can be utilized as auxiliary judgment basis.

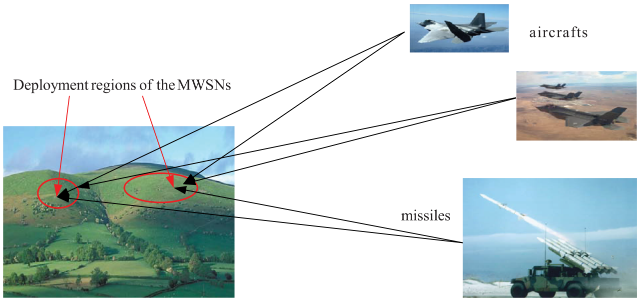

FIGURE 2. **Depolyment regions of MWSNs.**

The traditional abnormality diagnostic algorithms are to set the hard threshold value. Alerts or warnings would be triggered if the diagnostic value is larger than the hard threshold value. The advantage of these algorithms is that they are easy to be actualized in IEWS, the disadvantage is that the false-alarm probability is too high. In recent years, machine learning technique has been deeply studied [19]. After training tremendous data, these machine learning algorithms can achieve excellent performance by comparing and recognizing abnormal behaviors from a tremendous amount of monitoring data automatically. However, because of their large computational complexity for training data, these algorithms can not be executed in mobile devices efficiently. Thus some other techniques or theories have to be taken to deal with this problem. Then the application containing machine learning technique embedded in mobile devices can be executed in an efficient way.

For online and offline data analysis, the MWSN and relaying nodes have limited computation, memory, energy and communication capabilities, thus an infrastructure has high-performance for massive storage and the ability for powerful and scalable computing is required, which is suitable for real-time processing and data storage [9]. As a promising technology, mobile cloud computing (MCC) using low energy consumption provides multiple aspects functions in a scalable and virtualized manner such as a flexible stack of software services, storage, and massive computing [10]. In MCC, the powerful configuration is not needed in mobile devices such as large memory capacity or high CPU speed, since all tasks can be stored and processed in the cloud, which includes tremendous data and complicated computing. MWSN, cloud and mobile devices can be integrated seamlessly via 5G infrastructure and Internet. However, between the cloud controller and the data center, the wire optical cable can be used to improved the transmission rate and the capacity of channel.

Relaying nodes or mobile BSs serve as gateways for MWSN and have access to the Internet through 5G-link or WiFi. Part of processing of sample data can be taken in relaying nodes or mobile BSs before continuing to forward the data. The Primary Node (PN) of MWSN coordinates with gateways. Then the offloading strategy is made decision. The PN can offload data collected by MWSN to the cloud accordingly through gateways. Once the request from PN is received, the cloud controller will schedule the early warning task on virtual machine (VM), diagnostic results will be delivered to mobile devices of commanders and the control center. The powerful VM resources of cloud provide great potential to run IEWS, the location-based services, etc. The control center, commanders, soldiers and even anti-aircraft missiles communicate with cloud by various interfaces such as PCs, mobile phones and other mobile devices.

In order to improve the ability of analysing and processing data, the hybrid cloud computing architecture is introduced [12]. The cloud is divided into private and public cloud. The sensitive data such as the monitoring data of MWSN, military secret documents and some top secret plans are stored and processed in local private cloud to guarantee security. The testing, maintenance and updating of cloud system which are not sensitive can be done in public cloud. The parclose between private and public cloud has to be set, which plays the role as the firewall. Some non-sensitive data in private cloud can be transformed into public cloud through the parclose. The data requests and responses between private and public cloud have to be permitted by the firewall.

The data authorization application plays an important role in data authorization and authentication, the data which does not belong to the battlefield surveillance system can not access the cloud. In order to separate the data of battlefield surveillance system from other complex tremendous data, the data of battlefield surveillance system is marked with uniform and sole identification. Other data which does not have the identification can not access the cloud. Commanders are offered with different levels, which have different permissions to access the cloud. For example, defense minister of a country has higher permission than commanders, who can make critical military decisions such as the nuclear weapon launch and some decisions of top secrets, etc. They all have sole identifications, which can be identified by data authorization application. Soldiers and anti-aircraft missiles have sole identifications as well. Abnormalities observed by soldiers can be delivered to the cloud for analysis, and the machine fault of anti-aircraft missiles can also be delivered to the cloud as well. Then based on the data authorization application, the data identification can be guaranteed.

B. CLOUD NETWORKING FOR MULTIPLE BATTLEFIELD SURVEILLANCE SYSTEM

Current cloud computing infrastructure services provide on-demand compute and storage facilities for mobile end-user services. However, services are always provided by a single provider, only some fundamental services beyond the data centre can be achieved. Based on the rapid development of wireless network, an evolution is in progress for cross-provider infrastructure for large scale cloud services. i.e., the data centre and network operators interact through defined interfaces to provide seamless virtual infrastructure. The virtual cloud infrastructure in a multi-administrative domain scenario forms cloud networking [5]. The characteristic of cloud networking should be adaptive, reliable, scalable and autonomous. Cloud networking provides more powerful ability to analyse and process data. Thus multiple battlefield surveillance systems in different regions can be connected together to form the cloud battlefield surveillance networking. However, the problem that only limited information is disclosure to support the cross-domain connection has to be solved.

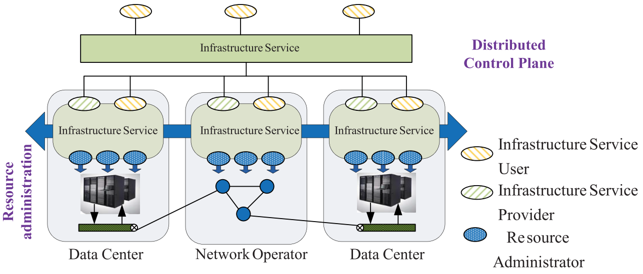

FIGURE 3. **Cloud networking architecture.**

As shown in Fig. 3 [5], three main classes of interface are defined as the distributed control plane (DCP), resource administration and infrastructure service; three primary roles are defined as resource administrator, infrastructure service provider and infrastructure service user. Based on the infrastructure service, infrastructure service provider and infrastructure service user can interact with each other. The administrative domain including virtual or physical equipment can be managed by resource administrator. Through resource administration interfaces, the resource administrator can create virtual infrastructure. Protocols and interfaces of different administrative domains are collected by the DCP. It plays the most important role in across administrative domains, which is used to implement coordinating actions.

The infrastructure service provider may choose to collaborate with other infrastructure service providers that span their domains, thus virtual infrastructures can be extended to a great extent. Virtual resources can be connected at their boundaries to give the impression of a single virtual infrastructure. For the infrastructure service user, only a single service control interface is adopted, and the user's infrastructure from cross administrative domains and its control are managed collaboratively by different providers. The user has no feelings about the integration of cross administrative domains. The deployment of compute and storage resources is based on the network operator equipment. A composable model of virtual networks called a flash network slice (FNS) is exploited among these federated infrastructures [5]. FNS can be linked across administrative boundaries, which is introduced as a network resource type. Virtual infrastructures can be partitioned into isolated administrative domains by strong ability of FNS and can be realised on multiple network technologies.

Based on the cloud networking for integrating multiple battlefield surveillance system, virtual resources across administrative domains can be integrated seamlessly. The commanders such as defense minister and general can realize the information for all battlefields immediately and conveniently. All the data among among different administrative domains can be shared through the network operator based on cloud networking.

C. THE EMERGENCY CONDITION

The most important purpose of this battlefield surveillance system is to deal with the emergency condition. When enemy aircrafts and missiles are coming, MWSN can detect the electromagnetic wave, acoustical and infrared signals sent by enemy objects. The abnormal data will be delivered to delaying nodes from the forward node of MWSN. If the data is delivered to mobile BSs, some per-processing technologies could be executed before forwarding the data. then the processed data will be delivered to Internet through BS in the military base using 5G link. In this emergency condition, the data related to enemy aircrafts and missiles are transmitted to cloud service directly, the data authorization is not needed. In order to separate the abnormal data from the normal data, some labels or pre-coding strategies can be used in the abnormal data, then the abnormal data can bypass the data authorization application. These data are delivered to cloud service directly. All the abnormal data analysis and processing are completed rapidly in the cloud based on IEWS. Alerts or warnings can be sent to the commanders and the control center immediately. The commander can realize the information about the number of enemy aircrafts and missiles, the flight route of enemy aircrafts and missiles and other important parameters by executing the application of mobile device. Based on MCC technique, applications with large computational complexity are offloaded to the cloud. Anti-aircraft missiles can be waken up to intercept enemy aircrafts and missiles by the order of commanders control by mobile device.

For the battlefield surveillance system, the most important part is MWSN, whose responsibility is to collect the data related to enemy aircrafts and missiles. In order to improve the efficiency of spectrum usage, CWN is adopted. Cognitive radio (CR) is a promising approach to achieve open spectrum sharing flexibly and efficiently [20], [21]. CWN may not only depend on CR. Then CR can be made some extention to network, and DSA is used as the spectrum access scheme. DOAs of coming enemy aircrafts and missiles are important parameters for predicting flight route of enemy aircrafts and missiles. Thus DSA technique and DOA estimation algorithm are two important issues which have to be solved for intercepting enemy aircrafts and missiles accurately.

III. DYNAMIC SPECTRUM ACCESS TECHNIQUE

From the spectrum access perspective, CWN consists of primary nodes (PNs) and secondary nodes (SNs). PNs have the priority to occupy the spectrum. In wireless environment, SNs of spectrum opportunistically access the spectrum based on activities of PNs in a DSA based network. Only when the frequency band of adjacent PNs has the gap of tolerable interference, then SNs are allowed to access the gap spectrum band. The gap spectrum band is called ''spectrum hole'', which is defined as a piece of spectrum not occupied by any PN at a given time in a given geographic area. However, the spectrum hole between the frequency spectrum of PNs can not be used without limitation. The principle is that SNs' communication should not affect PNs' communication. The tolerant interference of PNs can be well described by concept of interference temperature [22], which is a metric used to quantify the interference in the wireless environment. For the spectrum band of interest, the interference temperature provides an accurate measure for an acceptable level of RF interference. Therefore, it plays an important role in the opportunistic spectrum sharing, which can be a metric used to quantify the interference.

For a given frequency spectrum band, the potential RF energy introduced by SNs can be limited by the ''cap'' which is defined as the interference temperature of PNs. In order to have an intuitional impression about the spectrum hole, the sketch map in shown in Fig. 4.

A. THE CONTROL CLOUD

Different frequency bands of PNs are pre-specified, which are limited by interference temperature. The spectrum hole can be detected by spectrum sensing performed by SNs. The communication channels of SNs are extracted from these spectrum holes. However, the spectrum hole is different from channel. A spectrum hole can be any size, which is a continuous spectrum space. A channel is agreed by communication entities, which is a pre-specified spectrum. Among channels, the control channel is the most important one, whose ability is to coordinate nodes of network. In [22], the control cloud

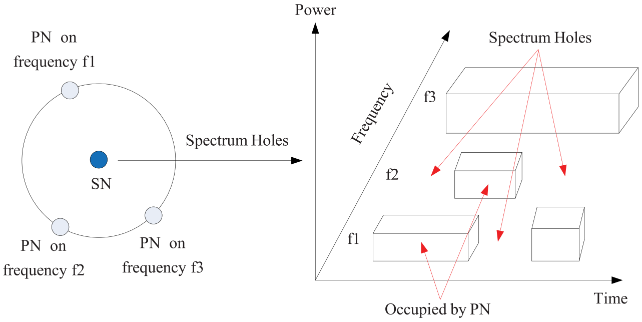

FIGURE 4. Spectrum hole.

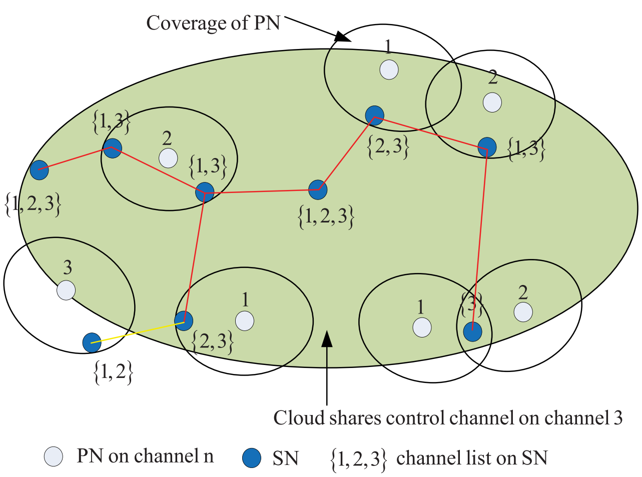

FIGURE 5. Control cloud in MWSNs.

concept was proposed. The neighbor SNs sharing a common control channel are collected together to form the control cloud. Based on the wireless and network environment, the size of control cloud can be changed dynamically. A common control channel is shared by the whole network, then the whole network can be controlled by a single control cloud. In other condition, multiple control clouds are coordinated to control the whole network. An intuitional example is shown in Fig. 5.

B. THE CLUSTER BASED MWSNs

In a large scale MWSN, there are lots of sensor nodes. Thus the cluster based method is adopted for MWSN, which is more manageable to control the spectrum access in a DSA scenario. A group of neighbor SNs forms a cluster. A cluster head controls the cluster, which is selected from this group of neighbor SNs. In general, this group of neighbor SNs is one-hop away from the cluster head. All SNs are controlled by the same control cloud. The control channel is called the master channel of that cluster. The cluster head has the responsibility for intra-cluster channel access control and inter-cluster communications. Based on the coordination of gateway nodes, clusters among MWSN can communicate with each other. Multi-hop links are used to deliver data messages from one cluster to another one. The function of a gateway node belonging to a cluster is that it can communicate with the node belonging to another cluster. Thus there are three classes of sensor nodes: the cluster head, the gateway node and the normal node. The inter-cluster communications are shown in Fig. 6.

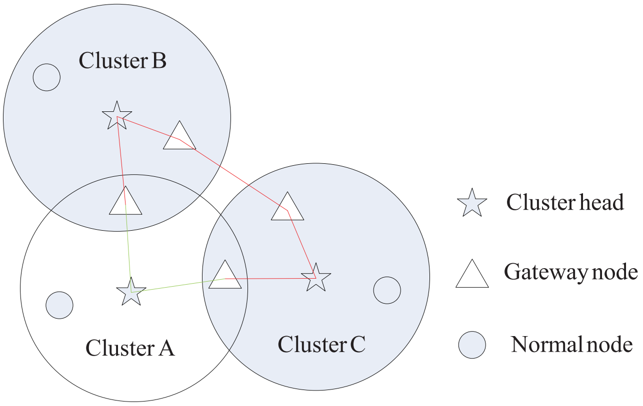

FIGURE 6. Inter-cluster communications in MWSNs.

The cluster head of Cluster A communicates with cluster heads of Cluster B and Cluster C through one-hop gateway nodes. When the cluster head of Cluster B communicates with the cluster head of Cluster C, no one-hop gateway nodes can connect two cluster heads. Thus, they communicate with each other through two-hop gateway nodes. The principle of cluster can be found in [22].

IV. DOA AND POLARIZATION ESTIMATION

In this section, a 1D DOA and polarization parameter estimation algorithm with uniform linear array (ULA) is proposed. Based on Fourier transform, this method is extended to arbitrary topology structure. Finally, we extend this method to 2D DOA and polarization parameter estimation.

A. PROBLEM FORMULATION

Assume that P completely polarized electromagnetic waves impinge on a polarization sensitive array (MWSN) composed of M mobile sensor nodes. These nodes can be disposed arbitrarily on a planar or conformal surface to collect the data of enemy targets. We introduce three complex vectors $\mathbf{V}_x$, $\mathbf{V}_y$ and $\mathbf{V}_z$. They stand for the measure voltages at each output port of the node of the MWSN, which correspond to excitation source of the unit electric field parallelling with x-axis, y-axis and z-axis, respectively. The output matrix, i.e., the voltage matrix generated at each output port of the MWSN, $X \in \mathbb{C}^{M\times K}$ for K snapshots can be written as

$$\mathbf{X}(\theta,\phi,\gamma,\eta,t) = \mathbf{A}(\theta,\phi,\gamma,\eta)\,\mathbf{S}(t) + \mathbf{N}(t), \quad t = 1,\ldots,K \tag{1}$$

where $\mathbf{A}(\theta,\phi,\gamma,\eta) \in C^{M\times P}$ is the manifold matrix, and the pth column $\mathbf{A}_p(\theta,\phi,\gamma,\eta) \in C^{M\times 1}$ of it can be expressed as

$$\mathbf{A}_p(\theta,\phi,\gamma,\eta) = \mathbf{V}_p(\theta,\phi)\,\Gamma_p(\gamma,\eta)\,\mathbf{a}_p(\theta,\phi) \tag{2}$$

where the voltage matrix is $\mathbf{V}_p(\theta,\phi) = \left[\mathbf{V}_h^p, \mathbf{V}_v^p\right] \in \mathbb{C}^{M\times 2}$, and its horizontal and vertical voltage components $\mathbf{V}_h^p$ and $\mathbf{V}_v^p$ can be respectively expressed as

$$\mathbf{V}_h^p = -\mathbf{V}_x \sin\phi_p + \mathbf{V}_y \cos\phi_p, \tag{3}$$

$$\mathbf{V}_v^p = \mathbf{V}_x \cos\theta_p \cos\phi_p + \mathbf{V}_y \cos\theta_p \sin\phi_p - \mathbf{V}_z \sin\theta_p. \tag{4}$$

$\mathbf{\Gamma}_p(\gamma,\eta)$ is the polarization factor vector

$$\Gamma_p(\gamma,\eta) \in C^{2\times 1} \tag{5}$$

where the polarization angle γ and phase η take values $0 \le \gamma \le \pi/2$ and $-\pi \le \eta < \pi$, respectively. $(\cdot)^T$ stands for transpose operator.

$\mathbf{a}_p(\theta,\phi) \in \mathbb{C}^{M\times 1}$ is the steering vector of the pth signal, and the mth entry of it can be written as

$$a_m\left(\theta_p,\phi_p\right) = \exp\left[jk\left(x_m \sin\theta_p \cos\phi_p + y_m \sin\theta_p \sin\phi_p + z_m \cos\theta_p\right)\right] \tag{6}$$

where x_m, y_m and z_m stand for the Cartesian coordinates of the mth sensor node, the wavenumber is $k = 2\pi/\lambda$. $\mathbf{S}(t) \in \mathbb{C}^{P\times K}$ is the complex signal matrix, and $\mathbf{N}(t) \in \mathbb{C}^{M\times K}$ is the additive white noise. Thus the problem is stated as follows: the output voltage matrix X of K snapshot number is given, the direction parameter $\left(\theta_p,\phi_p\right)$ and polarization parameter $\left(\gamma_p,\eta_p\right)$, $p = 1,\ldots,P$ are aimed to be estimated.

B. 1D DOA AND POLARIZATION ESTIMATION FOR ULA

For the sake of simplicity, the 1D condition is considered first. Assume all the sensor nodes and the far field incident signals are in the same plane ($\theta = 90°$). Thus (1) is simplified as

$$\mathbf{X}(\phi,\gamma,\eta,t) = \mathbf{A}(\phi,\gamma,\eta) S(t) + \mathbf{N}(t). \tag{7}$$

The pth column $\mathbf{A}_p(\phi,\gamma,\eta) \in C^{M\times 1}$ of it can be expressed as

$$\mathbf{A}_p(\phi,\gamma,\eta) = \mathbf{V}_p(\phi)\,\Gamma_p(\gamma,\eta)\,\mathbf{a}_p(\phi) \tag{8}$$

where the voltage matrix is $\mathbf{V}_p(\phi) = \left[\mathbf{V}_h^p, \mathbf{V}_v^p\right] \in \mathbb{C}^{M\times 2}$, and its horizontal and vertical voltage components $\mathbf{V}_h^p$ and $\mathbf{V}_v^p$ can be respectively expressed as

$$V_h^p = -V_x \sin\phi_p + V_y \cos\phi_p, \tag{9}$$

$$V_v^p = -V_z. \tag{10}$$

The mth entry of $\mathbf{a}_p(\phi) \in \mathbb{C}^{M\times 1}$ is expressed as

$$a_m\left(\phi_p\right) = \exp\left[jk\left(x_m \cos\phi_p + y_m \sin\theta_p\right)\right]. \tag{11}$$

Assume the array configuration is ULA, and the distance between the neighbouring sensor nodes is d, which is arranged along x-axis. Then (11) is simplified as

$$a_m\left(\phi_p\right) = \exp[jk(m-1)d\sin\phi_p], \quad m = 1,\ldots,M \tag{12}$$

where $x_m = (m-1)\,d$, ϕ_p stands for the angle between the pth incident signal and y-axis. Let

$$\begin{aligned}\mathbf{B}(\phi,\gamma,\eta) &= diag\{\mathbf{a}(\phi)\}\,\mathbf{V}(\phi)\,\mathbf{\Gamma}(\gamma,\eta)\\ &= \mathbf{W}(\phi)\,\mathbf{\Gamma}(\gamma,\eta)\end{aligned} \tag{13}$$

where $\mathbf{W}(\phi) = diag\{\mathbf{a}(\phi)\}\,\mathbf{V}(\phi)$. Based on the standard MUSIC algorithm, a scale cost function $D(\phi,\gamma,\eta)$ is defined as

$$\begin{aligned}D(\phi,\gamma,\eta) &= \mathbf{B}^H(\phi,\gamma,\eta)\,\mathbf{G}\mathbf{G}^H\mathbf{B}(\phi,\gamma,\eta)\\ &= \mathbf{\Gamma}^H(\gamma,\eta)\,\mathbf{W}^H(\phi)\,\mathbf{G}\mathbf{G}^H\mathbf{W}(\phi)\,\mathbf{\Gamma}(\gamma,\eta)\\ &= \mathbf{\Gamma}^H(\gamma,\eta)\,\mathbf{C}(\phi)\,\mathbf{\Gamma}(\gamma,\eta)\end{aligned} \tag{14}$$

where $(\cdot)^H$ stands for conjugate transpose. The eigenvalue decomposition (EVD) is taken on the sampling covariance matrix. The matrix $\mathbf{G} \in \mathbb{C}^{M\times(M-P)}$ is constructed by the eigenvectors corresponding to $(M-P)$ small eigenvalues. i.e., $\mathbf{G}$ is the noise subspace. $\mathbf{C}(\phi) = \mathbf{W}^H(\phi)\,\mathbf{G}\mathbf{G}^H\mathbf{W}(\phi) \in C^{2\times 2}$. The minimum of $D(\phi,\gamma,\eta)$ can be obtained via multiple dimensional ϕ,γ,η searching. For the standard MUSIC algorithm, it can be seen that the angle and polarization estimation problem converts the pure 1D angle searching into 3D searching, the computational complexity is tremendous.

It can be observed from (14) that if matrix $\mathbf{\Gamma}$ equals to the eigenvector corresponding to the minimum eigenvalue of matrix $\mathbf{C}$, then D can achieve the minimum value, i.e., the minimum eigenvalue of matrix $\mathbf{C}$. Since D is a nonnegative value, the minimum eigenvalue of matrix $\mathbf{C}$ is a nonnegative value as well. If $\phi = \phi_0$, i.e., the actual direction of the incident signal, then D equals to zero. Once the actual direction of the incident signal ϕ_0 is obtained, the EVD of the matrix $\mathbf{C}$ can be taken. The eigenvector $\hat{\mathbf{\Gamma}}$ corresponding to the minimum eigenvalue of matrix $\mathbf{C}$, which can be regarded as the estimator of $\mathbf{\Gamma}$.

For the ULA, let $z = \exp(jkd\sin\phi)$, (12) can be written in another form as

$$a_m\left(\phi_p\right) = z^{-1}, \quad m = 1,\ldots,M. \tag{15}$$

Thus we have

$$\begin{aligned}\mathbf{C}(\phi) &= \mathbf{W}^H(\phi)\,\mathbf{G}\mathbf{G}^H\mathbf{W}(\phi)\\ &= \mathbf{W}^H(z)\,\mathbf{G}\mathbf{G}^H\mathbf{W}(z) = \mathbf{C}(z).\end{aligned} \tag{16}$$

The DOAs of the incident signals can be obtained by solving the equation with respect to z as follows

$$f(z) = \det\{\mathbf{C}(z)\} = 0 \tag{17}$$

where $\det\{\cdot\}$ stands for the determinant operator. Let $\hat{\mathbf{q}}$ stands for the eigenvector corresponding to the minimum eigenvalue of matrix $\mathbf{C}$, the polarization parameter can be obtained

$$\begin{aligned}\hat{\gamma} &= \arctan\left(\hat{q}_2/\hat{q}_1\right),\\ j\hat{\eta} &= \ln\left(\frac{\hat{q}_2}{\hat{q}_1}\cdot\frac{\left|\hat{q}_1\right|}{\left|\hat{q}_2\right|}\right)\end{aligned} \tag{18}$$

where $\hat{q}_1$ and $\hat{q}_2$ stand for the first and the second entry of $\hat{\mathbf{q}}$, respectively.

C. 1D DOA AND POLARIZATION ESTIMATION FOR ARBITRARY ARRAY

Although the spectrum speaking searching is avoided by using Root-MUSIC method, this method can merely applied to ULA. Based on the Fourier transform, we extend this method to arbitrary array.

The function $f(\phi) = \det\{\mathbf{C}(\phi)\}$ is a periodic function with periodic 2π, which can be expanded based on Fourier series as

$$f(\phi) = \sum_{n=-\infty}^{+\infty} F_n \exp(jn\phi). \tag{19}$$

The Fourier coefficient F_n is expressed as

$$F_n \approx \frac{1}{2\pi}\sum_{l=-N}^{N} f(l\Delta\phi)\exp(-jnl\Delta\phi) \tag{20}$$

where $\Delta\phi = 2\pi\big/2N+1$ is the spatial sampling interval, $2N+1$ is the number of modes. Once F_n is obtained, the function $f(\phi)$ can be approximated as

$$\begin{aligned} f(\phi) &\simeq \sum_{n=-N}^{N} F_n \exp(jn\phi) \triangleq \tilde{f}(\phi) \\ &= \sum_{n=-N}^{N} F_n z^n \triangleq \tilde{f}(z) \end{aligned} \tag{21}$$

where $z = \exp(jn\phi)$. The angle information can be obtained by taking polynomial rooting on (21). It should be noted that the orders of (17) and (21) are different. The equation order of (17) is $2M-1$. However, the equation order of (21) is $2N+1$. In general, the order N of Fourier transform is larger than the number of sensor nodes M. Compared with (17), (21) has a higher computational complexity. The computation of (21) can be accelerated based on Fast Fourier Transform (FFT).

D. 2D DOA AND POLARIZATION ESTIMATION FOR ARBITRARY ARRAY

Similar as the 1D condition, the method proposed in last subsection can be extended to 2D condition. Define a matrix $\mathbf{B}(\theta,\phi,\gamma,\eta)$ as

$$\mathbf{B}(\theta,\phi,\gamma,\eta) = \mathbf{W}(\theta,\phi)\,\boldsymbol{\Gamma}(\gamma,\eta) \tag{22}$$

where $\mathbf{W}(\theta,\phi) = \mathit{diag}\{\mathbf{a}(\theta,\phi)\}\,\mathbf{V}(\theta,\phi)$. Then the cost function is written as

$$\begin{aligned} D(\theta,\phi,\gamma,\eta) &= \mathbf{B}^H\mathbf{G}\mathbf{G}^H\mathbf{B} \\ &= \boldsymbol{\Gamma}^H\mathbf{C}(\theta,\phi)\,\boldsymbol{\Gamma} \end{aligned} \tag{23}$$

The matrix $\mathbf{G} \in \mathbb{C}^{M\times(M-P)}$ is constructed by the eigenvectors corresponding to $(M-P)$ small eigenvalues. i.e., $\mathbf{G}$ is the noise subspace. $\mathbf{C}(\theta,\phi) = \mathbf{W}^H(\theta,\phi)\,\mathbf{G}\mathbf{G}^H\mathbf{W}(\theta,\phi) \in C^{2\times 2}$. If matrix $\boldsymbol{\Gamma}$ equals to the eigenvector corresponding to the minimum eigenvalue of matrix $\mathbf{C}$, then D can achieve the minimum value, i.e., the minimum eigenvalue of matrix $\mathbf{C}$. Since D is a nonnegative value, the minimum eigenvalue of matrix $\mathbf{C}$ is a nonnegative value as well. If $\theta = \theta_0$, $\phi = \phi_0$, i.e., the actual direction of the incident signal, then D equals to zero. Once the actual direction of the incident signal. i.e., elevation θ_0 and azimuth ϕ_0 are obtained, the EVD of the matrix $\mathbf{C}(\theta_0,\phi_0)$ can be taken. The eigenvector $\hat{\boldsymbol{\Gamma}}$ corresponding to the minimum eigenvalue of matrix $\mathbf{C}$, which can be regarded as the estimator of $\boldsymbol{\Gamma}$. In order to obtain the 2D angle information, the function

$$f(\theta,\phi) = \det\{\mathbf{C}\} = \det\{\mathbf{W}^H\mathbf{G}\mathbf{G}^H\mathbf{W}\}. \tag{24}$$

Since $f(\theta,\phi)$ is a a periodic function with θ and ϕ, it can be expanded based on Fourier series as

$$f(\theta,\phi) \approx \sum_{m=-L}^{L}\sum_{n=-K}^{+K} F_{mn}\exp(jm\theta)\exp(jn\phi). \tag{25}$$

The Fourier coefficient F_n is expressed as

$$\begin{aligned} F_n \approx \frac{1}{4\pi^2}&\sum_{l=-L}^{L}\sum_{k=-K}^{K} f(l\Delta\theta, k\Delta\phi) \\ &\times \exp(-jml\Delta\theta)\exp(-jnk\Delta\phi) \end{aligned} \tag{26}$$

where $\Delta\theta = 2\pi/2L+1$ and $\Delta\phi = 2\pi/2K+1$, $2L+1$ and $2K+1$ are the number of modes along the directions θ and ϕ, respectively. The 2D Fourier coefficient matrix $\mathbf{F}_{co} \in \mathbb{C}^{(2L+1)\times(2K+1)}$ can be obtained based on 2D FFT. In order to improve the resolution, the zero-padding method is applied to the 2D Fourier coefficient matrix

$$\mathbf{F}_{co} = \begin{cases} F_{mn}, & \mathit{for}\ |m| < 2L+1,\ \mathit{and}\ |n| < 2K+1 \\ 0, & \mathit{for}\ 2L+1 < |m| < L_0,\ \mathit{and}\ 2K+1 < |n| < K_0 \end{cases} \tag{27}$$

Usually, we have $L_0 \gg 2L+1$ and $K_0 \gg 2K+1$. Then $\hat{f}(\theta,\phi)$ can be obtained rapidly based on taking 2D FFT on the zero-padding 2D Fourier coefficient matrix $\hat{\mathbf{F}}_{co} \in \mathbb{C}^{L_0\times K_0}$. Based on MUSIC algorithm, the DOA of actual signal would make $\hat{f}(\theta,\phi)$ approximate to zero. Thus the 2D DOA estimators of P signals corresponding to the P spectrum speakings can be obtained by searching $1/\hat{f}(\theta,\phi)$.

Then the estimation results of multiple MWSNs can be fused together based on the distributed algorithm proposed in [24], which can improve the estimation accuracy. The principle is shown in Fig. 7.

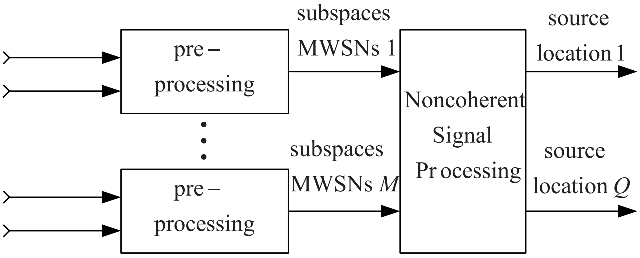

FIGURE 7. The fusion of multiple MWSNs.

However, the position error of the relative positions among the nodes is an important issue to solve. The authors can provide a method to deal with this problem. We can fix the nodes with a particular configuration. Then these nodes can be equipped with a mobile node which has a large power to carry them. The Global Position System (GPS) can be equipped with this mobile node, then the positions of these nodes can be confirmed more accurately. The trade-off is that we lose the flexibility of the MWSN and the energy consumption increases because of the implementation of the mobile node with a large power.

V. SIMULATION RESULTS

For the sake of simplicity, we only consider the 1D DOA and polarization estimation. In order to verify that the proposed method can be applied to arbitrary topology structure, we simulate the proposed method with a conformal structure, ten mobile sensor nodes are arranged on the surface of a non-uniform paraboloid. Ten nodes are symmetrically placed on the paraboloid of revolution with equation $y = -0.25x^2$. The arc length of this paraboloid is 10λ, the normal direction is $\phi = 90°$. The coordinates of sensor nodes are $(3.448\lambda, -2.973\lambda)$, $(2.309\lambda, -1.333\lambda)$, $(1.594\lambda, -0.635\lambda)$, $(1.184\lambda, -0.350\lambda)$, $(0.733\lambda, -0.134\lambda)$, $(-3.448\lambda, -2.973\lambda)$, $(-2.309\lambda, -1.333\lambda)$, $(-1.594\lambda, -0.635\lambda)$, $(-1.184\lambda, -0.350\lambda)$ and $(-0.733\lambda, -0.134\lambda)$, respectively.

Assume two narrow farfield signals impinge on the MWSN with directions $\phi_1 = 80°$ and $\phi_1 = 120°$. The polarization parameters of the first and the second signals are $(\gamma_1 = 30°, \eta_1 = 90°)$ and $(\gamma_2 = 50°, \eta_2 = 170°)$, respectively. The number of modes is $N = 60$. The length of Fourier series after zero padding is 4096. The snapshot number is 128. 500 independent trials are taken. The root mean square errors (RMSE) of different parameters versus signal to noise ratio (SNR) are depicted in Fig. 8, Fig. 9, and Fig. 10, respectively.

It can be seen from Fig. 8 that the RMSE of azimuth 1 is smaller than that of azimuth 2. This is caused by that the azimuth 1 is closer to normal direction compared with azimuth 2. The estimation accuracy of both azimuth angles increases as the SNR increases. However, the trend of the curve tends to plain. This is caused by that the direction patterns of different nodes are different. As shown in Fig. 9, and Fig. 10, the RMSEs of the polarization angle and phase have the similar characteristic with azimuth.

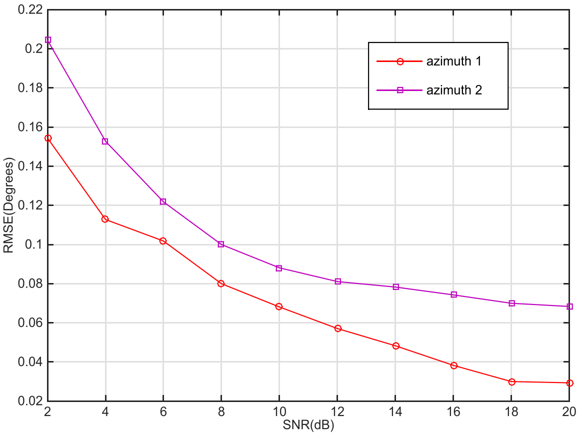

FIGURE 8. RMSE of azimuth versus SNR.

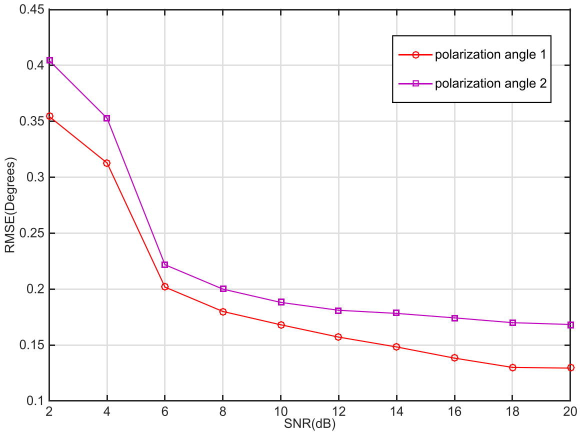

FIGURE 9. RMSE of polarization angle versus SNR.

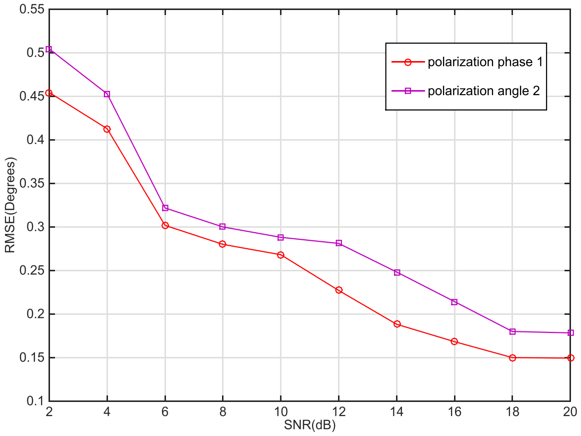

FIGURE 10. RMSE of polarization phase versus SNR.

VI. CONCLUSION

In this paper, the architecture of battlefield surveillance system is constructed based on MCC and 5G-link for both single cloud and cloud networking. In order to improve the efficiency of spectrum usage, CWN is adopted using DSA technique and cluster based method. In order to estimate the parameter information for enemy targets, three distributed DOA and polarization estimation algorithms for MWSN are proposed based on Root-MUSIC. The 2D Fourier coefficient matrix can be obtained based on 2D FFT, which has a low computational complexity. Since the environment of the deployment region is complexity, we will extend our previous work [25], [26] about conformal array into the parameter estimation of MWSN.

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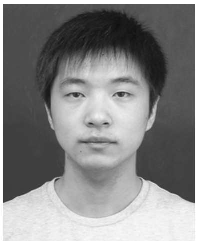

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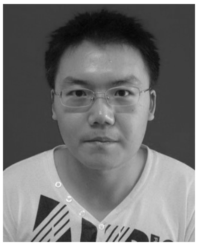

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