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## A survey of fault diagnosis for swarm systems

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Swarm systems have received increasing research attention in recent years and they can be found in many application areas as diverse as unmanned vehicle formation systems, multi-robot systems, sensor networks, etc. Reliability and safety are important issues in swarm systems, which can be improved by the fault diagnosis technology. In this paper, recent development of fault diagnosis algorithms for swarm systems is reviewed. The description of swarm systems is given, followed by characteristics of faults in swarm systems. Specially, faults in swarm systems are classified into topology faults and component faults. Then fault diagnosis algorithms for swarm systems are classified according to their architectures, fault types and approaches, respectively. Finally, several unsolved problems of fault diagnosis algorithms for swarm systems are highlighted.

**Keywords:** fault diagnosis; swarm systems; scalability; reliability

### 1. Introduction

Research on swarm systems has attracted much attention in recent years. A swarm system is a system that consists of multiple intelligent interconnected nodes and possesses swarm capability. Swarm systems can be found in nature and engineering areas. In nature, colonies, schools, flocks, herd, crowds, and society are all examples of swarm systems. Nodes in natural swarm systems are able to make better use of natural resources or escape from their enemies in a better way than a single node. Inspired by natural swarm systems, humans have designed many engineering swarm systems such as unmanned vehicle formation systems, multi-robot systems, sensor networks, etc. to achieve complex assignments. For instance, an unmanned airplane formation system is able to search survivors or detect enemies in larger areas than a single unmanned airplane (Miller 2006). Multi-robot systems are capable of providing service to patients in hospitals in a collaborative mode (Barea et al. 2009). Compared with a single sensor, wireless sensor networks have the ability to measure environment parameters in a cheaper and more reliable way (Chong & Kumar, 2003).

A swarm system consists of nodes and the topology of nodes. The main characteristics of a swarm system are intelligence of nodes, interconnection among nodes and swarm intelligence. The intelligence of nodes means that nodes can process data by themselves. The interconnection among nodes means that nodes are able to exchange messages with other nodes in a swarm system. The swarm intelligence is achieved by the collaboration and cooperation of nodes in a swarm system. Sensors in swarm systems possess

more functions than those in a single dynamic system. In swarm systems, sensors are classified into two categories, i.e. the link-sensor and the node-sensor. The former is able to measure the relative states between neighbor nodes. The latter is able to measure the states of the nodes where it is installed. This classification of sensors is helpful to study the problems in swarm systems and has never been mentioned before to our knowledge. The interconnection among nodes can be implemented in two ways, i.e. communication by which some information of nodes can be transmitted and link-sensors by which relative states between nodes can be measured.

Many issues on swarm systems have been addressed. Behaviors of natural swarm systems were investigated in Reynolds (1987), Toner and Tu (1998), and Nagy, Akos, Biro, and Vicsek (2010). In engineering areas, many results about swarm systems have also been reported in recent years. Five different formation flying control schemes were presented in Scharf, Hadaegh, and Ploen (2003, 2004). Consensus problems of single integral and double integral multi-agent systems were addressed in Cheng, Hou, Tan, and Wang (2011), Hu and Lin (2010) and Cheng, Wang, Hou, Tan, and Cao (2012). A control algorithm of swarm systems was proposed in Li, Duan, Xie, and Liu (2012), Wang, Cheng et al. (2011), and Chang, Chen, Chang, and Tao (2010). However, consensus algorithms and control schemes were achieved under the assumption of the normal operation of systems in the aforementioned literature. Faults have significant influences on the normal operation of a swarm system. The reliable operation of a swarm system

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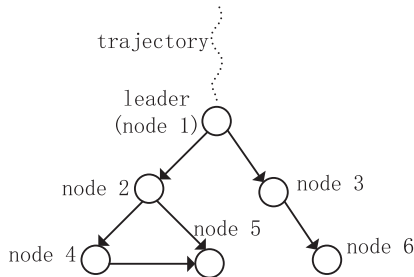


Figure 1. Leader–follower robots formation.

highly depends on the fault diagnosis algorithm which plays a critical role in detecting and isolating faults. Though fault diagnosis for swarm systems has been developed for many years, results on this research topic are very limited.

In this paper, the recent progress on fault diagnosis for swarm systems is surveyed. In Section 2, characteristics of faults in swarm systems are presented and classification for faults in swarm systems is proposed. In Section 3, we classify the fault diagnosis algorithms into different sorts according to three different criteria, respectively. In Section 4, several issues on fault diagnosis for swarm systems are highlighted.

## 2. Faults in swarm systems

Relationship between faults in different nodes is intricate in a swarm system. The coupling of node states is the main reason for the intricacy. Fault symptoms are thus transferred among neighbor nodes. For example, in a leader–follower robots formation as shown in Figure 1, a fault in node 2 will change the trajectory of node 2 and the local followers, which means that the fault symptom is transferred from node 2 to node 4 and node 5.

Faults in swarm systems can be classified into two types according to their influences. If a fault changes the topology, then the fault is termed as a *topology fault*. If a fault only affects actuators, node-sensors, or controllers of a node and does not change the system topology, the fault is termed as a *component fault*. Main examples of topology faults are communication link faults, link-sensor faults, and intrusions. Links between different nodes are broken and data are lost when the communication link faults happen. When an intrusion occurs in a swarm system, a node is lost or controlled by other nodes that do not belong to the system. Examples of component faults are actuator faults, node-sensor faults, and controller faults in nodes where they are installed.

## 3. The classification of fault diagnosis algorithms

A lot of issues need to be considered in the design of fault diagnosis algorithms for a swarm system. The architecture of an algorithm, faults which an algorithm isolates, and approaches on which a fault diagnosis algorithm is based

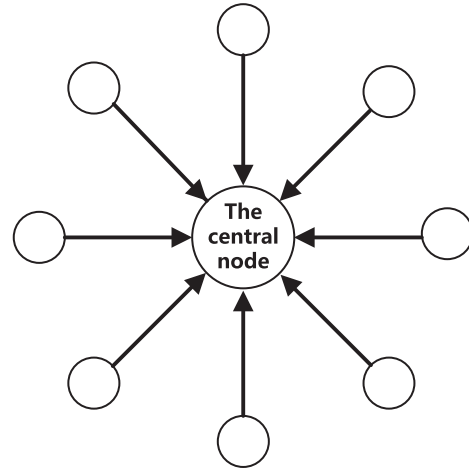


Figure 2. Centralized architecture.

are the top three factors that ought to be considered before designing a fault diagnosis algorithm for a swarm system.

### 3.1. Architecture

Some effective architectures of fault diagnosis algorithms for swarm systems have been proposed. These architectures can be divided into three categories, the centralized architecture where algorithms operate in only one node, the hierarchical architecture where algorithms are implemented in different layers, and the distributed architecture where algorithms are allocated in all nodes.

#### 3.1.1. Centralized architecture

Figure 2 depicts an overview of the centralized architecture of a fault diagnosis algorithm for a swarm system. Centralized fault diagnosis algorithms are installed in only one node of a swarm system or a virtual node which is not in the swarm system, for example, a base station. The node where the algorithm is installed is called the central node. It has to know the structure of the whole system in a centralized fault diagnosis algorithm. The other nodes are not able to perform self-diagnosis and they only send necessary messages to the central node, subsequently the central node can perform fault diagnosis for the whole system. Some examples of centralized fault diagnosis algorithms are as follows.

In Micalizio, Torasso, and Torta (2006), a centralized supervisor in a virtual node was designed to achieve the on-line monitoring and diagnosis for a multi-robot system, where a team of robots provided service to patients. It consisted of an on-line monitoring module, sensors, and a diagnostic interpretation module. The monitoring module was used to receive information from robots. Sensors were used to track the status of the robots and to measure partial environment variants. Then the diagnostic interpretation module explained the abnormal behaviors of the system

by exploiting a communicating automaton model of the system.

A centralized monitoring system was developed to detect malfunctions of robots in Wang, Shang, and Sun (2011) based on a back-propagation neural-network detector. The neural-network detector was trained using both positive and negative examples. The monitoring system collected data on positions and any formation errors of each robot to evaluate the working performance in terms of current and past states.

In Meskin and Khorasani (2009c), the problem of fault diagnosis for a network of the multi-agent system was addressed. The system owned a discrete-time communication link with a stochastic packet dropping effect. The communication was considered as a Gilbert–Elliott model and the entire network was modeled as a discrete-time Markovian jump linear system. A centralized  $H_\infty$  and geometric approach-based algorithm was developed to achieve actuator fault diagnosis for nodes in the network. There are also other examples of centralized fault diagnosis algorithms in Micalizio, Torasso, and Torta (2004), Ardissono et al. (2005), and Kalech and Kaminka (2005).

In a centralized fault diagnosis algorithm for a swarm system, the central node is able to perform fault diagnosis for the whole system. The other nodes do not make any fault diagnosis. What the other nodes do is to transmit their messages such as inputs and outputs to the central node. Therefore, a centralized fault diagnosis algorithm is able to make the best use of the knowledge of a system and achieve global optimization. However, disadvantages of the centralization are obvious. Both communication load and computation load are increasing rapidly as the number of nodes increases. Therefore, the scalability of a centralized fault diagnosis is far from satisfactory. Moreover, the whole system cannot achieve fault diagnosis in case of a malfunction of the central node. Hence, the reliability of the algorithm is poor.

### 3.1.2. Hierarchical architecture

A hierarchical architecture is introduced in order to improve the scalability and reliability of the centralized fault diagnosis algorithms. Different from the centralized architecture, a hierarchical algorithm is installed into a single node or all nodes of a swarm system. Local diagnosis information is pre-processed and then appropriate information is sent to the next layer for further diagnosis in a hierarchical framework. The hierarchical fault diagnosis is achieved by several layers and different layers accomplish different tasks in a swarm system. Figure 3 describes the architecture of a hierarchical fault diagnosis algorithm for a swarm system.

In Barua and Khorasani (2007), a hierarchical fault detection and isolation framework was presented for a spacecraft formation. In order to isolate faults, the fault diagnosis algorithm was designed based on the four-layer hierarchical decomposition of the formation flying system.

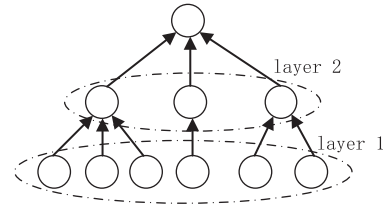


Figure 3. Hierarchical architecture.

The decomposition included a subsystem component level, subsystem level, system level, and formation level from low to high levels. Simple fuzzy rules were developed to describe the relationship between faults in different layers and to isolate faulty satellites in the formation. Based on the results of Barua and Khorasani (2007), a fuzzy reasoning-based algorithm was designed in Barua and Khorasani (2008) for a leader–follower formation flying with faults in attitude control subsystem components. The fuzzy rule in the algorithm modeled the relationship between the formation level and the subsystem component level. In Barua and Khorasani (2011a), a fuzzy-rule-based fault diagnosis scheme was further investigated for intermittent and non-abrupt faults in some components of a satellite formation flight. The performances of fault diagnosis for different levels were evaluated. The results showed that the fault diagnosis for formation level was more accurate than that for the subsystem component level. In Barua and Khorasani (2011b), a Bayesian network was applied to model the relationship between different layers in a satellite formation flight. Then the fault diagnosis was achieved by statistical inference.

In Valdes and Khorasani (2010) and Valdes, Khorasani, and Ma (2009), fault detection and isolation schemes based on hierarchical dynamic neural networks were designed. The scheme in Valdes and Khorasani (2010) consisted of three layers. The first layer and the second layer were developed based on the dynamic neural-network models of the single node and the formation, respectively. The third layer, integrated layer, combined the first two layer algorithms to achieve fault detection and isolation with high accuracy rates. Similar results can be found in Valdes et al. (2009) where there were only two layers in the algorithm.

The same approach was used in different layers of the above hierarchical fault diagnosis algorithms. Unlike those algorithms, in Meskin, Khorasani, and Rabbath (2010) and Carrasco, Nnez, and Cipriano (2011), different models or approaches were applied in different layers. In Meskin et al. (2010), a hybrid fault detection and isolation scheme was developed for a network of unmanned vehicles that were subject to large environmental disturbances. The proposed fault diagnosis algorithm consisted of two layers. The first layer was composed of a bank of continuous-time residual generators. The second layer was a discrete-event system fault diagnoser which was similar to a complex logic unit. The diagnoser was able to isolate faults and distinguish

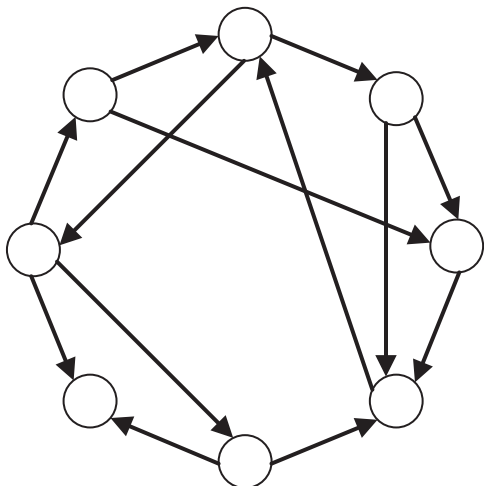


Figure 4. Distributed architecture.

faults from large external disturbances. In Carrasco et al. (2011), a two-layer architecture fault diagnosis scheme for a multi-robot system was presented. The first layer of the scheme was developed based on a bank of Kalman filters to achieve the diagnosis for actuator and node-sensor faults. The second layer was called the cooperative layer. It was able to isolate faults in link-sensors such as global positioning system sensors based on the statistical inference and sensor redundancy.

A hierarchical model is used to model a swarm system in a hierarchical fault diagnosis scheme. It is simpler than complex state space model. Moreover, due to the layered structure, different approaches can be applied in different layers. Algorithms can consequently be optimally implemented based on the capabilities and resources of nodes. However, the relationship between different layers is hard to model. Furthermore, the scalability and the reliability of the fault diagnosis algorithm are not satisfactory in a hierarchical architecture even though they are better than those in a centralized one.

### 3.1.3. Distributed architecture

Distributed architecture is proposed to improve the scalability of centralized and hierarchical fault diagnosis algorithms. Figure 4 shows the structure of a distributed fault diagnosis algorithm. All nodes in a swarm system are equipped with fault diagnosis algorithms in a distributed architecture. Every node is able to get the knowledge of the local structure of the swarm system and to receive messages from its neighbor nodes. Then these information is used in fault diagnosis algorithms. Fault diagnosis for a node is achieved in a collaborative way and the results of the algorithms in the neighbors of the monitored node are all needed. Distributed fault diagnosis for swarm systems has stirred a lot of research interest and some results have been reported in recent years.

In Daigle, Koutsoukos, and Biswas (2007), a distributed model-based qualitative fault diagnosis approach for formations of mobile robots was presented. The model of a mobile robot was a bond graph which described the physical components, sensors, and actuators. The communication among the robots was also modeled as bond graphs. The diagnosis scheme achieved fault detection by distributed Kalman filters. It then employed relative measurement orderings to achieve fault isolation. However, the qualitative model was lack of detailed information of the swarm system. Hence, faults which the scheme was able to isolate were very simple.

In Lchevin, Rabbath, and Earon (2007), a decentralized fault detection scheme was proposed to address a special problem in leader–follower formations of Almost-Lighter-Than-Air Vehicles (ALTAVs). The problem was that communication loss and component faults occurred simultaneously. In this scheme, each ALTAV was equipped with an  $H_2/H_\infty$  gain-minimization-based observer. The observer was designed based on simplified models of the neighboring ALTAVs. To illustrate the scheme in detail, assumed that the node  $i$ , node  $j$ , and node  $k$  were in a swarm system. Node  $j$  was a neighbor of node  $i$ , which meant that node  $j$  sent messages to node  $i$ . Node  $k$  was a neighbor of node  $j$  but not a neighbor of node  $i$ . An observer in node  $i$  was designed according to the residuals of node  $j$ . It also needed to dampen the impact of measurement noises and exogenous disturbances from node  $k$ . Then the fault diagnosis for the swarm system was achieved by such observers. Similar results can be found in Lchevin and Rabbath (2007). In Lchevin and Rabbath (2009), a novel scheme based on signal processing was proposed to achieve the detection of non-abrupt actuator faults in the formation of ALTAVs. For example, node  $j$  was the neighbor of node  $i$ , which meant that node  $j$  sent messages to node  $i$ . The scheme embedded in node  $i$  required at least two signals to detect a faulty behavior of node  $j$ . The signals included the heading angle trajectory of node  $i$  and that of a neighbor node of node  $j$  such as node  $k$ . The transients of the correlation caused by faulty behavior were able to be distinguished from those caused by the formation of the flight path changing. In Lchevin, Rabbath, Shanmugavel, Tsourdos, and White (2008), a scheme was designed to achieve the fault detection of both abrupt and non-abrupt faults based on the results in Lchevin et al. (2007) and Lchevin and Rabbath (2007, 2009).

In Meskin and Khorasani (2006), a bank of geometric approach-based distributed fault detection filters were designed for a spacecraft formation flying. Each local spacecraft was able to detect and isolate not only its own faults, but also the faults of other spacecrafts. The fault detection filter in a node was designed by determining an unobservability subspace that contained measurements from the neighbor nodes. The similar scheme was applied to a network of unmanned vehicles in Meskin and Khorasani (2009a). In Meskin and Khorasani (2009a), the solvability



conditions of distributed fault diagnosis based on the geometric approach were discussed. In [Meskin and Khorasani \(2009b\)](#), a distributed actuator fault detection and an isolation algorithm was proposed for a network of unmanned aerial vehicles. The network underwent imperfect communication channels among vehicles. The communication was modeled as a two-state Markov process. The residual was generated by the geometric approach. Necessary and sufficient conditions for generating a structured residual set were proposed by using unobservability subspaces. A constrained-state distributed Kalman filter was proposed to estimate the actuator fault in satellite formations in [Azizi and Khorasani \(2009a\)](#) and [Azizi and Khorasani \(2009b\)](#).

In [Shames, Teixeira, Sandberg, and Johansson \(2011\)](#), a bank of distributed unknown input observers were designed to achieve the fault detection for a network of interconnected second-order linear time-invariant systems. Furthermore, the existence of such observers was also established for various conditions on node interactions. In [Shames, Teixeira, Sandberg, and Johansson \(2012\)](#), a distributed fault detection and isolation scheme based on unknown input observers was proposed. The nodes in this swarm system were described as more complex models than double integrators. The scheme also indicated that measurements of the states of its two-hop neighbors were the minimum amount of information to achieve fault detection and isolation.

Only local information of the swarm system is able to be gained for a node in a distributed fault diagnosis algorithm. The algorithm is consequently not optimal. Fortunately, the scalability of the distributed architecture is higher than the other two. This fact means that communication loads and computation loads do not increase heavily with the rise of the number of nodes in a swarm system. Moreover, the distributed architecture is much more reliable than the centralized one and the hierarchical one.

### 3.1.4. Summary

The summary of different architectures of fault diagnosis algorithms, including their advantages and disadvantages, is listed in Table 1.

Different fault diagnosis algorithms are equal in some sense. [Meskin and Khorasani \(2009a\)](#) showed that solvability conditions of a distributed fault diagnosis problem were the same as those of a centralized scheme. The performance of the centralized architecture is worse than the other two. However, the properties of centralized fault diagnosis algorithms can be analyzed in a more convenient way than that of the other two.

## 3.2. Types of faults

According to the fault classification in Section 2, fault diagnosis algorithms for swarm systems can be classified into

Table 1. Summary of structures of fault diagnosis algorithms.

Classification	Advantages	Disadvantages
Centralized	Using global knowledge	Poor reliability; poor scalability; resource wasting
Hierarchical	Flexible approaches assignment	Low reliability; low scalability
Distributed	High reliability; high scalability; resource saving	Using local knowledge

two types, i.e. topology fault diagnosis algorithms and component fault diagnosis algorithms. In the former algorithms, models of swarm systems are simple and fault detection is achieved in a cooperative way. In the latter ones, diagnosis of component faults is achieved by more complex approaches.

### 3.2.1. Topology fault diagnosis

Similar to the intrusions in the internet, the communication network of a swarm system makes it vulnerable to malicious attacks [Teixeira, Sandberg, and Johansson \(2010\)](#). There is no state in the topology. Fault diagnosis for topology can only be achieved in nodes of a swarm system. Topology fault diagnosis algorithms are used to detect and isolate faults such as communication breaks and node intrusions. The algorithm in one node needs at least messages from other two nodes to perform fault diagnosis. Some research progresses on this topic have been made in recent years.

In [Izadi, Gordon, and Zhang \(2013\)](#), a simple cross-comparing way was proposed to identify inter-vehicle communication delays for a multiple-vehicle system. The delay arose from communication failures. In this approach, every vehicle received a normal signal from at least two neighboring vehicles. Then, by cross-comparing the delays, each vehicle was able to identify the fault.

In [Guo, Dimarogonas, and Johansson \(2012\)](#), two communication-based distributed schemes were proposed to detect the communication faults for a cooperative multi-agent system. In the first scheme, every node transmitted its own state and its control value to all its neighbors at each time step. The control value was computed by its own states and its neighbors' states. In the second scheme, the node transmitted its own absolute state and its neighbors' states to all its neighbors. By comparing the neighbor's actual control with the estimated control, the node was able to reach detection of the topology faults. The advantage of communication-based schemes is the significant reduction of required computational resources. Similar to diagnosing communication faults in a swarm system, the issue of detecting and isolating topology attacks in power networks was addressed in [Weimer, Kar, and Johansson](#)

(2012). In Weimer et al. (2012), the centralized and decentralized fault diagnosis algorithms were presented based on the stochastic hypothesis testing. In both algorithms, different models were developed under the assumption of different communication link breaks. The communication link break was detected by sampling the output of the system and further using the stochastic hypothesis testing algorithm. However, the scheme is unable to detect two or more simultaneous communication link breaks.

In Fagiolini, Valenti, Pallottino, Dini, and Bicche (2007), the problem of detecting uncooperative behaviors in a multi-agent system consisting of  $n$  vehicles was addressed. In the system, all agents were traveling along a two-lane automated highway. In normal operations, they obeyed the same cooperation protocol and the number of maneuvers in the protocol was finite. The agents were modeled as automata which included the cooperation protocol. The paper proposed distributed monitors installed in all agents. Each agent was able to judge whether its neighbors were cooperative or not by the monitor installed in it. For example, the monitor in node  $h$  was able to estimate the number of other neighbor nodes of node  $i$ . The estimation was achieved by using the protocol, the state of node  $i$ , and the states of nodes which were neighbors of node  $h$  as well as  $i$ . If there existed one or more neighbor nodes of node  $i$  to explain the actions of node  $i$ , then node  $i$  was normal. If there existed no neighbor nodes of node  $i$  to explain its actions, then it was intruded. In Fagiolini, Pellinacci, Valenti, Dini, and Bicchi (2008), based on the results of Fagiolini et al. (2007), the monitors were able to share the collected information to overcome their sensing limitation. The shared information was about the same monitored node. Then the monitors used the information to estimate the states of the monitored node. These monitors reached an agreement on the estimated states when the topology of the swarm system was connected and the operator of the estimated states was idempotent. In Fagiolini, Babboni, and Bicchi (2009), the detection capability of monitors was further improved. The monitors collected information of monitored nodes at different time instants. A dynamic state observer was designed to estimate states of the monitored nodes. Fault detection was reached by comparison between the estimated states and the observed states.

In Franceschelli, Egerstedt, and Giua (2008), a novel scheme was proposed to achieve the fault diagnosis for a swarm system. The swarm system was controlled by a consensus algorithm. The nodes in the swarm system was modeled as a single integrator dynamics. A motion probe was proposed in the scheme, which is a maneuver executed by either a single node or a team of nodes. In the scheme, the motion probes must be able to preserve desirable properties such as keeping the invariance of the state of the system centroid. Then they were able to identify faulty agents in a swarm system by changing their values. They can also be used for fault recovery by canceling out fault impacts on the

behavior of the non-faulty agents. In Franceschelli, Giua, and Seatzu (2009), motion probes were applied to fault detection for a sensor network. A heuristic algorithm was used to find nodes with suspected behaviors. Then motion probes were applied to confirm the faulty nodes within the suspected nodes.

In Pasqualetti, Bicchi, and Bullo (2007), a technique based on unknown input observers was proposed for the intrusion detection problem of a swarm system. The intrusion was modeled as an external input of the system. The paper showed that if the topology was 2-connected then the faulty nodes were able to be detected. An embedded filter was also designed to estimate the states of the other nodes by using the local information from the neighbors. The paper also showed that the estimation rate was related to the number of the neighbor nodes. A more detailed conclusion was reached in Sundaram and Hadjicostis (2011). The conclusion presented the relationship between the number of the detectable malicious nodes and the topology of a swarm system. The node in the swarm was modeled as a linear iteration. It updated its value to be a weighted average of its own previous value and the value of its neighbors. The paper showed that when the number of malicious nodes was  $f$  or less, a node was able to detect the faults of all nodes if the node had at least  $2f$  vertex-disjoint paths from all other non-neighboring nodes.

The models of nodes are simple in algorithms of topology fault diagnosis. These algorithms do not need too many computer resources. The efficiency of the algorithms is thus satisfactory. The topology fault diagnosis is not an exclusive issue in swarm systems. Any systems which have communication mechanisms such as the internet are also faced with the problem. Therefore, the topology fault diagnosis for swarm systems is able to inspire fault diagnosis for other similar systems.

### 3.2.2. Component fault diagnosis

Swarm systems are also endured component faults such as actuator faults, node-sensor faults, and controller faults except topology faults. If systems immediately take action when component faults happen, these faults only influence local nodes. In algorithms of component fault diagnosis, models of nodes are always complex so that components can be described in detail. These models include state space models, transfer functions, etc. These algorithms are consequently more complex than topology fault diagnosis algorithms. Some results are shown as follows.

In Semsar-Kazerooni and Khorasani (2009), three kinds of actuator faults were considered. These faults included effectiveness loss faults, float faults, and lock-in-place faults. The influence of faults on the stability and the consensus of a swarm system were presented. When an effectiveness loss fault happened, the stability and the consensus of the system was not influenced, but the convergence rate changed. In the presence of float-type faults, the swarm

system was not able to maintain the consensus but the stability was guaranteed. Moreover, healthy nodes adapted themselves to the changes in the faulty node. Under the condition of the lock-in-place faults, the stability was guaranteed if the open-loop matrix of the faulty agent was stable.

In [Valdes et al. \(2009\)](#), a dynamic neural-network-based fault diagnosis scheme was developed for thrusters in formation flying of satellites. In [Meskin and Khorasani \(2006\)](#), filters based on geometric fault diagnosis methodology were designed to achieve actuator fault detection and isolation. In [Azizi and Khorasani \(2009a\)](#), a distributed Kalman filter scheme was proposed to estimate the actuator faults for a deep space formation flying.

The fault isolation is so precise that the location of the fault can be found easily in algorithms of component fault diagnosis. However, these algorithms are resource consuming. Fault diagnosis algorithms for component faults in swarm systems are much more complex than those for a single dynamic system. Usually, the node is only able to get the relative information instead of the absolute information in swarm systems. The difficulty increases when fault symptoms in other nodes are transmitted to the node. Moreover, the real-time requirement of the algorithm is rigid in order that fault tolerant control can be timely undertaken to avoid serious consequences.

### 3.2.3. Summary

In general, topology faults and component faults have a different influence on a swarm system. A topology fault usually affects two or more nodes at the same time. In contrast, a component fault only affects the node where it is installed on the occurrence of the fault. The node performing topology fault diagnosis needs the information of the neighbor nodes and that of nodes which does not belong to its neighbors. However, the node performing the component fault diagnosis only needs the information of its neighbor nodes for the most part.

Table 2 shows advantages and disadvantages of topology fault diagnosis algorithms and component fault diagnosis algorithms. A novel idea to achieve fault diagnosis for swarm systems is to combine topology fault diagnosis schemes with component fault diagnosis schemes. For example, in [Teixeira et al. \(2010\)](#), a distributed scheme using observers was proposed to detect and isolate both kinds of faults. The communication faults were described as actuator faults and sensor faults. The sufficient condition for the existence of unknown input observers was that the

topology of the system was connected. The combination of two kinds of schemes is able to make good use of their advantages to achieve resource saving and precise fault isolation.

### 3.3. Approaches of fault diagnosis algorithms

Fault diagnosis for dynamic systems has been developed for many years since the year 1971 when the Kalman filter-based fault diagnosis algorithm was proposed in [Beard \(1971\)](#). Fault diagnosis algorithms were reviewed in [Willsky \(1976\)](#) and [Frank \(1990\)](#). In this section, we refer to the classification of fault diagnosis for dynamic systems in [Zhou and Hu \(2009\)](#) to classify fault diagnosis algorithms for swarm systems. The fault diagnosis algorithms thus can be classified into two types according to the approaches on which fault diagnosis algorithms were based. The two types are the qualitative algorithms and the quantitative algorithms.

Qualitative fault diagnosis algorithms apply qualitative models of the system to analysis the cause of faults. These algorithms are easy and are widely used. Furthermore, the simplicity of these algorithms makes them time and resource saving. However, diagnosis results of the qualitative algorithms are unreliable when the system is complex. Quantitative algorithms apply quantitative information of systems to reflect the inconsistency between the operating system and the normal system. The quantitative information includes the state space model of systems, data of systems, etc. Though quantitative algorithms are more complex than the qualitative ones, they are more reliable.

#### 3.3.1. Qualitative approaches

In qualitative approaches, fault diagnosis is achieved in qualitative ways such as expert systems, communication automata, and so on. These schemes are simpler than quantitative ones because they do not need precise models of systems.

In [Barua and Khorasani \(2008, 2011a\)](#), fault diagnosis based on the fuzzy rule was used for a satellite formation flying. Fuzzy rules were used to describe the relationship between different layer faults. Then they were used to diagnose the component faults and to isolate faulty satellites in the formation. The model is simple. However, the building of the model needs the cooperation of too many experts. Moreover, the results of the fuzzy rule-based reasoning are a bit uncertain. In [Khalil, Bagchi, and Nina-Rotaru \(2005\)](#), a communication-based fault diagnosis scheme was proposed. For example, node  $i$  was the neighbor node of node  $j$  and node  $h$ , which meant that node  $i$  sent messages to node  $j$  and node  $k$ . Node  $j$  was the neighbor of both node  $h$  and node  $k$ . In the scheme, when node  $i$  sent a data packet to node  $j$ , node  $h$  also received the packet. Then node  $j$  transmitted the packet to node  $k$  and node  $h$ . Then node  $h$  was able to monitor node  $j$  by comparing the packet

Table 2. Summary of topology fault diagnosis and component fault diagnosis.

Classification	Advantages	Disadvantages
Topology	Simple; efficient	Not precise
Component	Precise	Complex



which node  $i$  transmitted and the packet which node  $j$  transmitted.

Though qualitative fault diagnosis algorithms are not precise, the simplicity makes them resource and time saving.

### 3.3.2. Quantitative approaches

In quantitative approaches, models of swarm systems and data are needed to design fault diagnosis algorithms. Quantitative approaches are widely used in fault diagnosis of swarm systems. They can be classified into two sorts, i.e. model-based approaches and data-driven approaches Zhou and Hu (2009).

In Ilyas, Lim, Lee, and Park (2008), a federated unscented Kalman filter was designed to achieve fault diagnosis for a multiple-satellite formation flying in the low earth orbit. In Ilyas, Lee, and Park (2008), federated hybrid extended Kalman filters were proposed to realize fault diagnosis for the same application as Ilyas, Lim, et al. (2008). The approaches based on the Kalman filters are able to deal with the system with state noises and measure noises. Observer-based fault diagnosis algorithms for swarm systems can also be found. In Meskin et al. (2010) and Meskin and Khorasani (2006, 2009a, 2009b), fault diagnosis were achieved by observers designed based on the geometric approach. Fault diagnosis was reached by unknown input observers in Shames et al. (2011, 2012). Kalman filter-based approaches and observer-based approaches are called model-based approaches. Faults in these approaches are always described as the actuator faults. Fault diagnosis is achieved by analytical redundancy in these approaches. These approaches are able to reach accurate fault diagnosis results. However, the accurate model of the system is hard to build, which limits the application of the model-based fault diagnosis.

Data-driven methods are also broadly used in the design of fault diagnosis algorithms for swarm systems. A machine learning algorithm such as clustering analysis was used for intrusion detection in wireless sensor networks in Loo, Ng, Leckie, and Palaniswami (2006). A clustering algorithm was used to build a model of normal traffic behavior. Then this model was used to detect abnormal traffic patterns. It was also able to detect attacks that had not been seen previously. The dynamic neural network is another example of the machine learning algorithm. In Valdes and Khorasani (2010) and Valdes et al. (2009), the dynamic neural network was designed to model the dynamic properties of thrusters in the satellites. Then it was used to perform fault diagnosis for a formation of satellites. It is easy to build the dynamic neural model in case of sufficient data. Nevertheless, the data of the faulty system are hard to gain in practice, especially when unknown faults happen. The approaches based on dynamic neural networks are not suitable for swarm systems where the data are hard to get. The signal processing is another widely used data-driven

method to design fault diagnosis algorithms for swarm systems. In Wu and Saif (2007), a bank of wavelet networks were constructed to isolate and to estimate faults in a multiple-satellite formation flying. The wavelet network was proposed as an alternative to a neural network by approximating the nonlinear observer. The proposed three-layer wavelet network comprised an input layer, a wavelet layer, and an output layer. When faults occurred, all the wavelet networks generated a large amount of chattering. Then the chattering was used to indicate the occurrence of the fault with proper threshold values. In Wang, Chang, and Chen (2009) and Lchevin and Rabbath (2009), statistical analysis was used to deal with fault diagnosis for a swarm system. In Wang et al. (2009), an efficient collaborative sensor fault detection scheme was proposed based on statistical analysis. In the scheme, the results of a homogeneity test were used to identify the faulty nodes within the sensor network. Their quantized messages were able to be filtered out when the parameters of interest were estimated in the normal case. However, the mean square error increased dramatically if the information received from the faulty sensors was not excluded from the estimated process. The statistical analysis was based on this fact. Though the performance is significantly better than a conventional estimation scheme, it is only suitable to be applied in special environments.

### 3.3.3. Summary

Figure 5 describes the classification of the current fault diagnosis algorithms for swarm systems according to approaches. The advantage of qualitative approaches is time and resource saving. The advantage of quantitative approaches is precise isolation of faults. The combination of the two different approaches will generate a more efficient tool to achieve fault diagnosis.

## 4. Unsolved problems of fault diagnosis for swarm systems

Fault diagnosis for swarm systems is a new area in control community and compute community. Though a few primary results have been achieved, research is far from mature and a lot of issues are challenging. In this section, we list some research topics on fault diagnosis for swarm systems.

- (1) *Fault diagnosis for swarm systems with heterogeneous faults.* The problem that topology faults and component faults happen simultaneously is common, but there are few approaches toward this topic. Though some results on this issue have been reported such as Franceschelli et al. (2008), the approach in the literature is only able to detect and to isolate actuator faults by designing observers that are robust to topology faults. Fault diagnosis in the case that topology faults and component faults happen simultaneously is worth investigating.

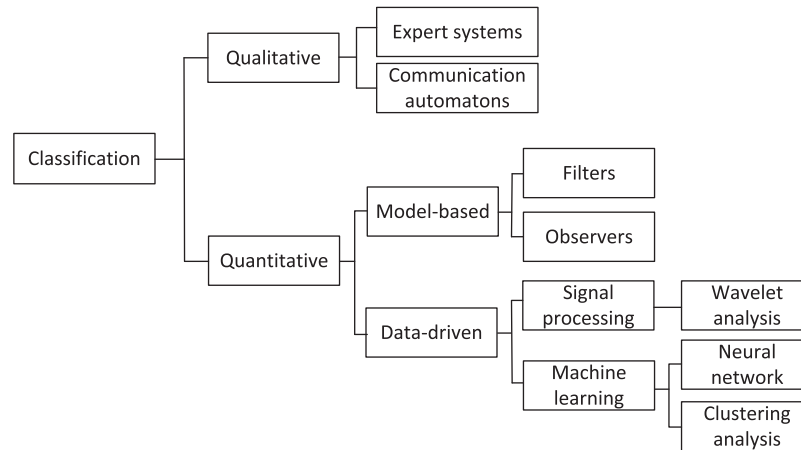


Figure 5. The summary of qualitative approaches and quantitative approaches.

- (2) *Fault diagnosis for swarm systems with switching topologies.* In a swarm system whose topology is always changing to maintain the control performance, the fault diagnosis algorithms should have the capability to distinguish whether there are faults or the swarm system is in normal topology switching operation. For a swarm system whose topology is switching according to its controller, it is interesting to consider its fault diagnosis problem.
- (3) *Fault diagnosis for swarm systems with heterogeneous nodes.* In military areas, the formation of warships and unmanned aerial vehicles is very useful, but fault diagnosis algorithms for such systems are rarely reported. In Valenti, Bethke, Fiore, How, and Feron (2006), health management was embedded into a test bed and was used to execute many different mission scenarios. Though the implementation of the hardware was described, fault diagnosis algorithms were not mentioned. How to perform fault diagnosis for swarm systems with heterogeneities nodes needs to be addressed.
- (4) *Fault diagnosis for swarm systems with a large number of nodes.* When the number of the nodes in a swarm system is very large, new problems arise. For example, the asynchronism may disturb the fault diagnosis results and communication conflicts increase. Though the scalability of distributed fault diagnosis algorithms is better than that of the hierarchical and centralized ones, the current distributed algorithms are not capable of solving this issue. Fault diagnosis algorithms for swarm systems with a large number of nodes remains unexploited.

## 5. Conclusions

In this paper, a general description and characteristics of swarm systems have been summarized. Faults of swarm

systems have been classified into topology faults and component faults. Three different kinds of classification for fault diagnosis algorithms for swarm systems have been presented. Finally, some interesting research topics on the fault diagnosis for swarm systems have been highlighted.

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