IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received March 23, 2019, accepted March 28, 2019, date of publication April 4, 2019, date of current version April 18, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2909283

Efficient Matching of Multi-Modal Sensing Nodes for Collaborative Sense Optimization of Composite Events

JUN LIU[1], FEI YUAN[1], JIANHUA WANG[2], AND XU LU[3]

[1]School of Automation, Guangdong Polytechnic Normal University, Guangzhou 510665, China
[2]School of Electronic Engineering, South China Agricultural University, Guangzhou 510642, China
[3]School of Computer Science, Guangdong Polytechnic Normal University, Guangzhou 510665, China

Corresponding author: Xu Lu (bruda@126.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 61802073, in part by the Scientific Research Project of Guangzhou City under Grant 201707010482, in part by the Young Innovative Talents Project of Universities in Guangdong Province under Grant 2017KQNCX121, and in part by the PhD Start-up Fund of Natural Science Foundation of Guangdong Province, China, under Grant 2016A030310335.

ABSTRACT Composite events are sense maximizes collaboration through multiple sensors. Efficient matching of multi-modal sensing nodes in multi-composite events is always a thorny problem. In this paper, the composite event sensing model is first proposed, and then the collaborative-sense problem of multi-modal sensing nodes is translated into a binary matching problem. For these multi-class sensors and multi-class compound events scene, a pruning-grafting and parallel strategy be adopted, which can speed up the traversal speed and find the maximum matching edge quickly. For multi-nodes selection, the distance of the composite event constraints into binarily weighted matching. A collaborative-sense intelligent matching algorithm is suggested. It takes collaborative in various kinds of nodes matching combining with the distribution of the composite event itself around the nodes. Combined with the random distribution of various sensor nodes and composite events, the matching rate of some sensor nodes is sacrificed for the overall event efficiency. Compare to parallel algorithms, it has another effect on perceived efficiency. Finally, by comparing with other algorithms, CSSMA and other proposed algorithms have a certain advantage in the inclusive sense efficiency. In terms of composite events collaborative-sense, this work has nice theoretical significance and practical value.

INDEX TERMS Collaborative sense, composite events, bipartite graphs, binary match, pruning-grafting.

I. INTRODUCTION

The accurate and comprehensive observation of the physical world is the application basis of Internet of things (IoTs) and Cyber-Physical Systems (CPS [1], [2]. In the physical world, all kinds of sensing nodes are deployed in the monitoring area to observe all aspects to obtain the physical world information accurately, which usually contains a number of heterogeneous sensor networks. These heterogeneous sensor networks contain various multimodal sensing nodes with different sense, computing and communication capabilities. It is of great significance to coordinate and monitor the complex dynamic process of the physical world. It descriptions of the physical world are often represented by events [3], [4]. The data obtained by multi-modal sensing node are called multimodal data, and the event model is proposed based on multi-modal data and time and space attribute. Sensors and networks are deployed to more precisely monitor the physical world. And for different applications, the objects of monitoring are also different, such as deployed in the border to prevent invasion, deployed in the indoor to prevent fire accident, deployed in the factory workshop, is to monitor a process error resulting in product quality [5]. All of the above monitoring objects can be defined as events, and multiple types of sensors are required for collaborative observation [6]. In these scenarios, a certain type of event concerned by the application system requires joint judgment of multi-class sense data. A single sense data is useless to the

The associate editor coordinating the review of this manuscript and approving it for publication was Mu-Yen Chen.

system and cannot predict the occurrence of certain events. People do not care about the value or accuracy of a specific data. Therefore, how to optimize and mobilize multi-class sense nodes to monitor the occurrence of this kind of complex events is extremely important. Events are divided into atomic events and composite events [7], [8]. Atomic events are composed of distinct modal data. And composite events composed of multiple atomic events. It can describe the composite state of the physical world. Therefore, how to collaborative sense of composite events is an important problem to realize physical observation.

The existing researches on composite event monitoring are mostly based on event coverage. In [9], it studies how to optimize the coverage of heterogeneous nodes to minimize the deployment cost, and proposes the approximate algorithm and the precise algorithm of the greedy strategy. Literature [10] for sensor hole repaired in heterogeneous sensor networks, it studies how to repair the sense hole through the mobile node relocation. The research object is the optimal matching between the heterogeneous sensor nodes and the sense hole, while composite events are different from sense holes. The application of IoT monitoring in the physical world is described and processed in the form of events, which can be combined with the idea of software services such as [11]. For composite event monitoring, a distributed composite detection event method based on clustering mechanism proposes in [12]. The algorithm focuses on composite event monitoring. An Internet-of-Things (IoT) Cooperative System (IoT-CS) based on local Event-Driven response is developed in [13]. The collaboration here is based on the service cooperative of the upper application. The problem of active node selection for localization tasks, on the Internet of Things (IoT) sensing applications, is addressed in [14]. Weight factors are integrated into a two-phase active node selection mechanism that uses genetic and greedy algorithms to select optimum groups for localization tasks.

Bipartite graph is the basic problem of discrete mathematics. Many scholars have studied it [15]–[17]. A novel framework for restricted 2-matchings close to Hamilton cycles proposed in [15]. Based on the Hosoya index, it determines the maximum matching energy among all connected bipartite graphs [16]. Minimum Cost Bipartite Perfect Matching Problem with Conflict Pair Constraints (MCBPMPC) on bipartite graphs proposed. A specially tailored branch-and-bound (B&B) algorithm is adopted in [18].

Many real-world complex networks have a naturel bipartite structure. It describes the connection in a bipartite network that is suitable for the nature of today's huge data networks in [19]. A hybrid bipartite graph based recommendation algorithm for mobile games in [20]. This paper proposes a bipartite graph based recommendation algorithm PKBBR (Prior Knowledge Based for Bipartite Graph Rank). The problem of ranking vertices of a bipartite graph is studied, based on the graph's link structure as well as prior information about vertices in [21]. The problems of quasi-matchings and semi-matchings in bipartite graphs are considered with applications in wireless sensor networks in [22]. Nodes collaborative sense of composite events is actually a matching problem. Numerous scholars have conducted beneficial research on this problem [23], [24], [27]. In [16], it research optimization configuration of the optimal relay selection according to the theory of cognitive wireless network optimization of resource allocation problem. Equivalent to MWBM, through Hungary method instead of statistical expectation, is more effective than the traditional method. Azad proposed a maximum cardinality matching algorithm in [25]–[27], which can share memory in parallel, achieve good performance and scalability, and obtain the maximum cardinality matching in the two parts. A novel hierarchical node deployment strategy is proposed for static wireless sensor network data flow collection in [28]. A probabilistic analysis method based on a complete matching random graph is established. In order to bridge the scalability problem of integer programming, a bipartite matching algorithm with maximum weighting is designed to overcome the scalability problem of integer programming in [29].

The monitoring of composite events needs the cooperative sense of multiple multi-modal sensing nodes. The above is mostly aimed at the idealization of the composite event model in the scene, and many models are modeled as coverage problems. Secondly, the multi-class of data is involved in the composite events. It requires multi-class sense nodes to be coordinated. In fact, it is a matching optimization problem built on the composite event and the multi-modal sensing nodes. In view of this, this paper studied how to collaborative various kinds of sensing nodes under random composite events. It mainly involves multimodal sensors between nodes and composite events matching optimization. And maximize overall perceived effectiveness. According to the problem model, it was converted to binary matching problem. And then puts forward cooperative sense optimization algorithm. Finally it compares the algorithm performance, through the experiment showed that the collaborative sense algorithm can increase the overall efficiency.

The monitoring of composite events requires the cooperative work of multiple multi-modal sensing nodes. The above is mostly aimed at the idealization of the composite event model in the scene, and many models are modeled as coverage problems. Secondly, the multi-class of data is involved in the composite events. It requires multi-class sense nodes to be coordinated. In fact, it is a matching optimization problem built on the composite event and the multi-modal sensing nodes. In view of this, this paper studied how to collaborative various kinds of sensing nodes under the composite under random events. It mainly involves multimodal sensors between nodes and composite events matching optimization. And maximize overall perceived effectiveness. According to the problem model, it was converted to binary matching problem. And then puts forward cooperative sense optimization algorithm. Finally it compares the algorithm performance, through the experiment showed that the collaborative sense algorithm can increase the overall efficiency.

Our main contributions in this paper are as follows:

1. Composite Events Collaborative Sense Model: In this paper, the problem of multi-modal sense nodes' collaborative sense of composite events is proposed. This is the first time that, from this point of view, to address this problem.

2. MS-BFS-Pruning-Grafting algorithm: We propose a new matching search method based on tree pruning-grafting mechanism. It reduces the repetitive work of multiple phases and named MS-BFS-Pruning-Grafting. It integrated the advantages of multi-source and single source. It lies a foundation for solving the problem of the sensor node matches the compound event.

3. Smart Matching Algorithm for Collaborative Sense Optimization of Composite Events(CSSMA): Based on the previous analysis, combine the distance of the composite event constraints into binary weighted matching. A collaborative sense intelligent matching algorithm is proposed. It takes collaborative in various kinds of nodes matching combining with the characteristics of the composite event itself around the nodes.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. COMPOSITE EVENTS COLLABORATIVE SENSE MODEL

Assume the sensors deployment area is defined as A. Different k types of multimodal sensors are deployed. The sense radius of each sensor is $r_1, r_2, \ldots, r_k$ respectively. The number of nodes in each class is $n_1, n_2, \ldots, n_k$. Composite events monitored by the system are $E(e_1, e_2, \ldots, e_n)$. The composite event co-sense model composed of different k types of nodes is defined as $D = \{n_1, n_2, \ldots, n_k\}$. While $\forall i \in \{1, 2, \cdots, k\}$, n_i is represented the number of the i sensor nodes in the system.

Definition 1: atomic event: $e\left(data, \hat{t}\right)$.

While *data* represents a perceptual data, $\hat{t}$ represents the data collection moment, and both of them determine the occurrence of atomic events together. Composite events are usually composed of several atomic events. Composite rules of composite events are constructed according to application requirements, mainly including the requirements for the synthesis of these atomic events.

Definition 2: composite events are: $E(e_1, e_2, \ldots, e_n) = \Psi(e_1, e_2, \ldots, e_n)$.

Composite events are composed of several atomic events e, which Ψ represent the logical relations of several atomic events and describe the composite rules of composite events. The concrete form of composite events depends on the specific application requirements.

As shown in Fig. 1, Composite event E_1, E_2, E_3 are sensed by multi-modal sense nodes $S_i^a, S_i^b, S_i^c, S_i^d$. However, only the event E_1 is accomplished by the collaborative sense of four types of sense nodes $S_i^a, S_i^b, S_i^c, S_i^d$.

Definition 3: composite event sense quality is:

$$\Delta_i = \delta_{j1} \oplus \delta_{j1} \oplus \cdots \oplus \delta_{jl}, S_i = \{j_1, j_2, \ldots, j_l\} \tag{1}$$

Among them, composite events are composed of multiple atomic events, and its quality monitoring is determined by monitoring the quality of atomic events. While, δ_{ji} represents corresponding monitoring quality of atomic events or confidence, and on the basis of synthetic rules to compute composite event monitoring quality.

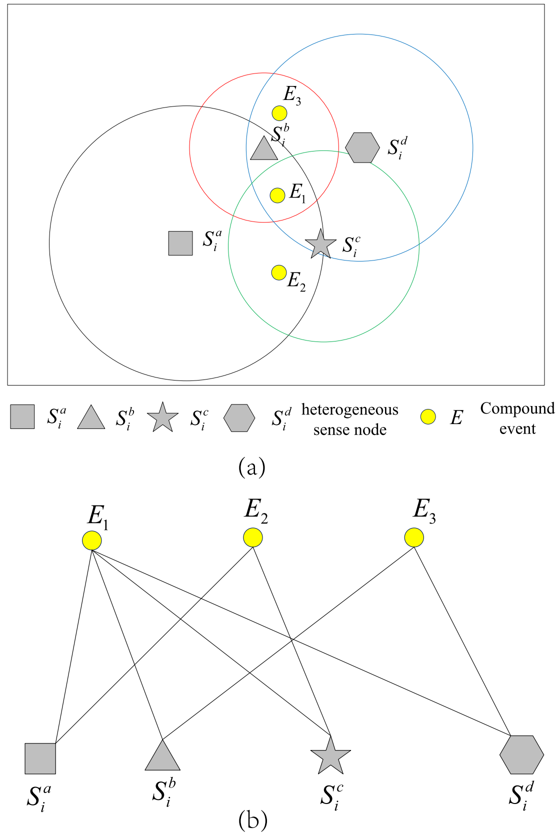


FIGURE 1. The collaborative sense model of composite events of heterogeneous sensing nodes. (a) Multi-sensor nodes and multi-compound events are randomly distributed. (b) The sense relation of the sensors node to composite events.

B. PROBLEM FORMULATION

In this paper, the problem of multi-modal sense nodes' collaborative sense of composite events is defined as follows:

Definition 4 (Maximize Sense Effectiveness problem: MSEP): k class nodes are deployed to sense composite events $E(e_1, e_2, \ldots, e_n)$. Each type of nodes distributed in area randomly. Assume that the cost of each nodes are $c_1, c_2, \ldots, c_k$ and total cost constraint C. Find the best collaborative method $D = \{n_1, n_2, \cdots, n_k\}$ which achieved maximum sense effectiveness with no more than overall cost constraints.

$$\max \Delta_E = E(\Delta) = \sum_{i=1}^{N} P_i \Delta_i \tag{2}$$

$$s.t. \sum_{i=1}^{k} c_i n_i \leq C, \text{ where: } i = 1, 2, \cdots, k, n_i \in \{0, 1, 2, \cdots\} \tag{3}$$

while: $P_i = \prod_{j\in S_i} p_j \prod_{j\notin S_i}(1-p_j) = \prod_{j\in S_i}(1 - e^{-\frac{\pi r_i^2 n_i}{A}}) \prod_{j\notin S_i} e^{-\frac{\pi r_i^2 n_i}{A}}$. P_i P is the probability of event. A is the sensed area.

III. COLLABORATIVE SENSE EVOLUTION OF COMPOSITE EVENTS

It is assumed that the monitoring area of multi-type sensing nodes s and multiple composite events e is distributed in area A evenly. The perceived quality of each composite event is defined as $\Delta_i = \delta_{j1} \oplus \delta_{j1} \oplus \ldots \oplus \delta_{jl}$. It needs the multi-type senses to be coordinated to detect the occurrence of the event, as shown in Figure 2. However, each observation capability of the random distributed multi-type sense nodes is different, and one of nodes can only be used to monitor one of the composite events in the range of its observation capability.

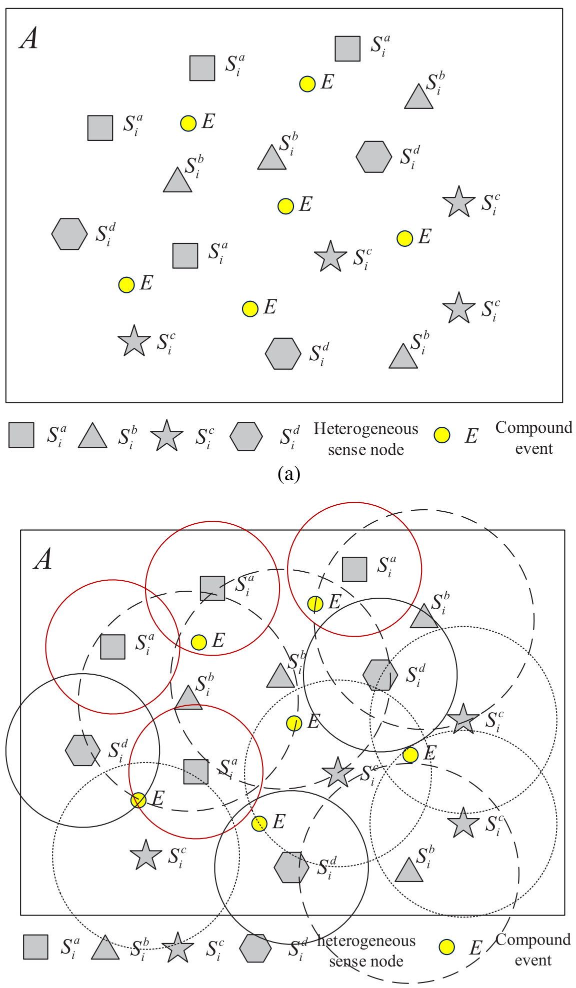


FIGURE 2. Heterogeneous sensing nodes and composite events are randomly distributed in the monitoring area. (a) Random distribution of multimodal sensing nodes and composite events.. (b) Composite events are covered by various sensing nodes with different sense radius.

Therefore, two adjacent composite events such as $\{e_i, e_j\}$, at the same time, both need one kind of sense nodes S^κ. And the sensing nodes around the composite event there are

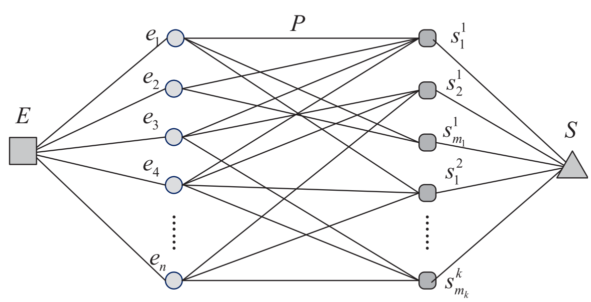


FIGURE 3. A bipartite graph between composite events and multi-modal sensing nodes.

multiple $\{s_1^\kappa, s_2^\kappa, \cdots, s_t^\kappa\}$. How to optimize matching such sense nodes and composite event is to research on this thesis. Namely composite events require multiple different types of sense nodes to collaborative sense of composite events. It needs composite event matching with multimodal sensors. The above optimization problem can be converted into a binary matching problem. And binary matching is the important problem in graph theory and combinatorial optimization.

It is assumed that E is composite events set $\{e_1, e_2, \cdots, e_n\}$. S is a multi-modal sense nodes set. Composite event requires multi-modal sensing nodes to make collaborative sense based on composite event combination rules. The multi-modal sensing node set is $S = \{s_1^1 \cdots s_{m_1}^1; s_1^2 \cdots s_{m_2}^2; s_1^k \cdots s_{m_k}^k\}$. There are k class nodes. The corresponding number of different sensors is m_k respectively.

It can be transformed into a graph $G(V, P)$, which contains the composite event set E and multi-modal sense node set S, as shown in Fig. 3. If a composite event e_i requires some kind of sense node s^j, and there is a kind of sense node around it, an edge p^γ is formed between them. All the edges constitute a set P.

Each composite event e_i has a variety of sense nodes s_j^i around it. The composite events in the monitoring area correspond to multiple sensory nodes. This requires the collaboration of surrounding nodes to complete the monitoring of composite events. In the case of binary matching, each class of sense nodes and composite events are a set of matching relationships. So the matching relationship between the same class of perceptual nodes and the composite events is analyzed first. As shown in the Fig. 4, (a) a binary graph, (b) is a weighted binary graph, and (c) is the maximum matching.

Due to distances between different sense nodes and composite events are also different, so their sensed effectiveness also are different. The matching problem of multi-modal sensing nodes and composite events can also be transformed into the ***Maximum Matching Problem of Weighted Bipartite Graph in Collaborative Sense of Composite Events***.

IV. OPTIMIZATION ALGORITHM BASED ON WEIGHTED BINARY GRAPH MATCHING

A. THEORETICAL BASIS

The following analysis is used to analyze the matching problem of bipartite graph. Alternate paths refers to the

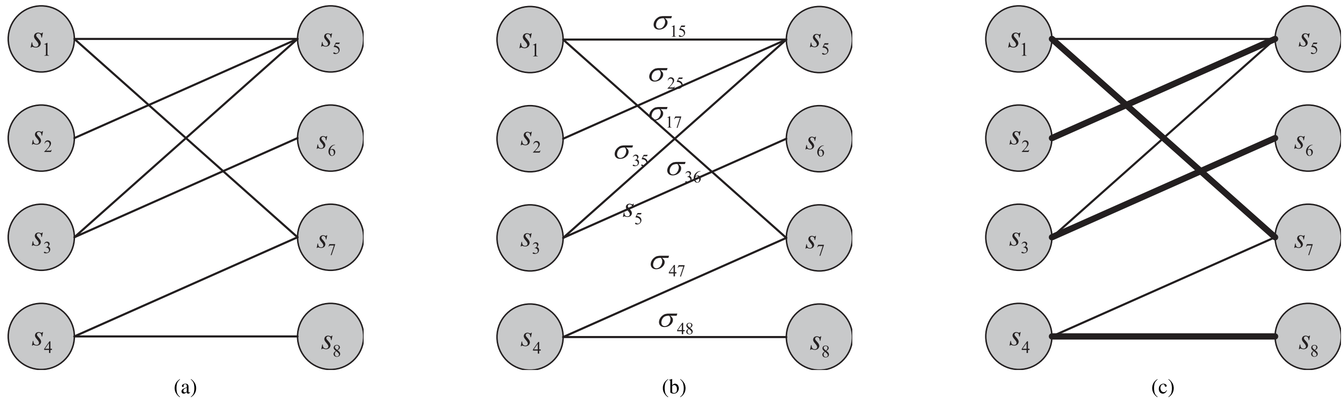


FIGURE 4. Binary matching process graphs. (a) Binary graph. (b) weighted dichotomy. (c) Maximum matching.

path that is formed from an unmatched point, which is followed by non-matching edges, matching edges, and non-matching edges. An augmented path refers to an alternate path from an unmatched point to alternate paths, if another unmatched point (the starting point does not count). As shown in Fig. 5(a)(b), it forms an augmented path. As shown in Fig. 5(c). Solid lines edges represent an alternating tree T(x_0). Broken lines Edges represent an augmenting path P=($x_1, y_1, \ldots, x_k, y_k$). There are matched and unmatched vertices in small circle. Thick lines represent matched edges and thin lines represent unmatched edges. Fig. 5(c) represents a plausible situation that T(x_0) and P have an edge in common.

B. THE MOST WEIGHT AUGMENTED PATH ALGORITHM

In this paper, the weight is different, and the most weight match is searched. Therefore, when expanding by augmenting path, it needs to combine the greedy strategy to search for the most weight matching edges in each search. Therefore, the most weight augmenting path algorithm based on greedy strategy can be proposed. The pseudocode is as follows Algorithm 1.

Algorithm 1 The Most Weight Augmented Path Extension Algorithm Based on Greedy Strategy

Input : **G(X, Y)**, **M** ;
Output: The most weight augmented path **M'**;
Let $M' = M, G' = G$;
Select a M'-Expose Vertex r, let $T = (\{r\}, \varnothing)$;
Start with the smallest number, and then run BFS for unmatched points to find the matching edge with the maximum weight.
While there is $vw \in E'$ let $v \in B(T)$, $w \notin A(T)$;
Case: $w \notin V(T)$, w is M'-Expose;
Used vw augmented M';
Extending M' is a match M of G;
Used $M' \to M$ and $G' \to G$;
Return M' and Stop.
END

The above is a single source algori1thm. In our scenario, the model can be abstracted as multi-source graph. Algorithms based on multi-source graph searches (i.e., multi-source or MS algorithms) are more suitable for this kind of scenario. However, it has a significant weakness that multiple source algorithms have repeated searches at mismatched vertexes [30]. Because, search trees of MS are constrained to be vertex-disjoint to allow concurrent augmentations.

C. THE MS-BFS-PRUNING-GRAFTING ALGORITHM

To address this weakness of MS, a tree pruning-grafting mechanism that reduces the repetition work of multiple phases is presented and it named MS-BFS-Pruning-Grafting integrated the advantages of MS(multi-source) and SS(single source). It demonstrates better serial and parallel performance that other existing algorithms [25], [27].

Consider a maximal matching in a bipartite graph shown in Fig. 6(a).The unmatched S vertices s_1 and s_2 and creates two vertex-disjoint alternating trees $T(s_1)$ and $T(s_2)$. Thin lines represent unmatched edges and thick lines represent matched edges. Matching nodes are connected by matched edges. (b) A forest with two trees $T(s_1)$ and $T(s_2)$ created by MS-BFS algorithm [31]. The edges (s_1, e_2), (s_3, e_3), (s_4, e_5) are scanned but not included in $T(s_1)$ to keep the trees vertex-disjoint. Unvisited vertices shown in Subfig.(a) did not take part in the current BFS traversal. (c) The current matching is augmented by the augmenting path (s_5, e_3), (s_6, e_5). $T(s_1)$ remains active since no augmenting path is found in it, while $T(s_2)$ becomes a renewable tree. (d) Vertices e_3 and e_5 along with their mates are grafted onto $T(s_1)$. The vertices s_5 and s_6 form the new frontier.

A alternating trees are rooted at unmatched vertices S. The frontier F grows by the alternating forest. It is a subset of S vertices. Each visited E vertex will be marked. It is a part of a single tree. *parent*$[e]$ is the parent of a vertex e in E. A vertex s is visited from the mate. *root*$[s]$ is included the root of the tree. *leaf*$[x]$ is included unmatched leafs of

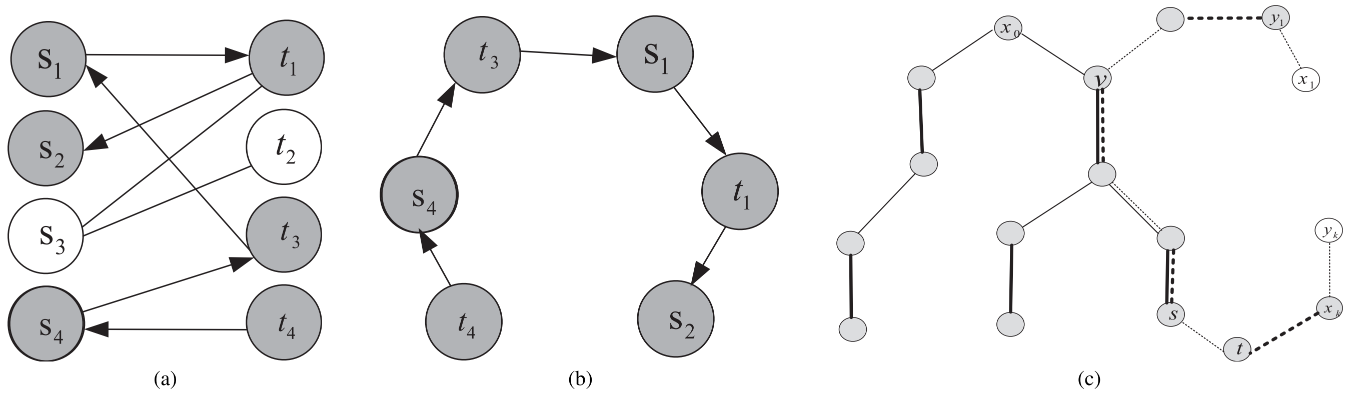


FIGURE 5. Augmented paths. (a) Binary matching path search. (b) The most augmenting path. (c) An alternating tree T (x_0) and an augmenting path P.

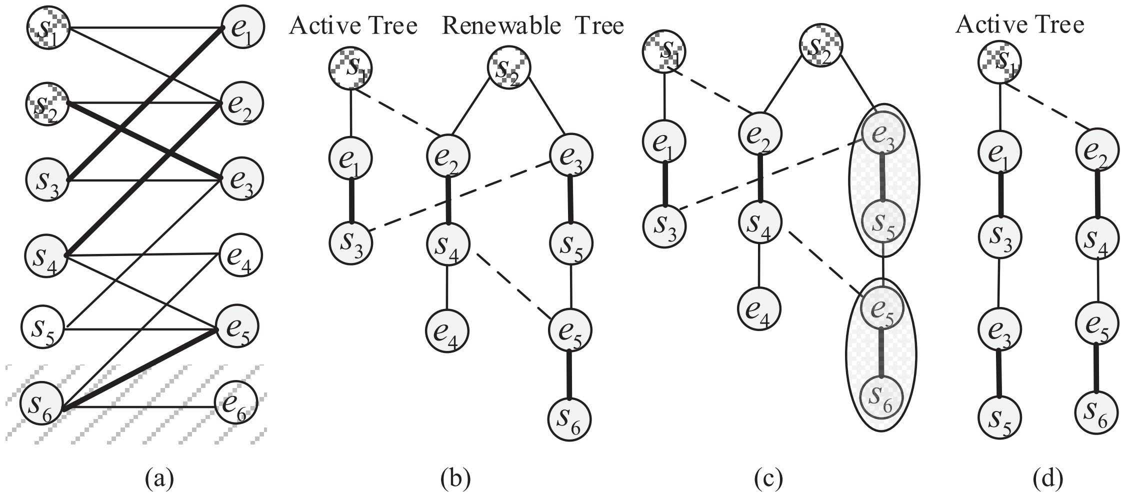


FIGURE 6. Tree-pruning-grafting mechanism. (a) A maximal matching in a bipartite graph. (b) Alternating BFS forest. (c) Tree pruning. (d) Tree grafting.

root[*s*]. The *parent*, *root* and *leaf* are set to -1 for a vertex out of tree. Each iterations in Algorithm 3 is can divided into three steps: 1. search for a set of vertex-disjoint augmenting paths by MS-BFS, 2. Expand the maximum match by augmenting paths, 3. rebuilding a tree by Pruning-Grafting mechanism.

We evaluate the performance of parallel matching algorithms (MS-BFS-Pruning-Grafting) on a representative set of bipartite graphs. It is from the University of Florida sparse matrix collection [32] and a randomly generated RMAT graph. The algorithms to compare them together include MS-BFS-Pruning-Grafting, GA and KM (Kuhn and Munkres) algorithm. KM algorithm is KM algorithm is a classic perfect matching algorithm.

As shown in Figure 7, we compared the matching rate and running time. SM-GA is based on the greedy strategy, which runs the fastest and takes the least time on the same scale. The parallel matching algorithms (MS-BFS-Pruning-Grafting) is able to find more matches due to its pruning strategy. In large-scale bipartite graph search, the time advantage is obvious due to KM algorithm.

D. SMART MATCHING ALGORITHM FOR COLLABORATIVE SENSE OPTIMIZATION OF COMPOSITE EVENTS(CSSMA)

The above algorithm is matches the most weight values in the binary graph based on greedy strategy. However, composite events are various types, and the following is a study of the most weight matching algorithm for the composite event. First of all, we introduce a parameter with the weight binary graph which can be converted into a binary matrix $W\left(x_i, y_j\right)$. If some of them are no edge existed, the corresponding edge weight is 0. w_{ij} represents the weight between sense nodes and events.

$$W\left(x_i, y_j\right) = \begin{bmatrix} w_{00} & w_{01} & \cdots & w_{0n} \\ w_{10} & \cdots & \cdots & w_{1n} \\ \cdots & \cdots & \cdots & \cdots \\ w_{m0} & & w_{mn-1} & w_{mn} \end{bmatrix} \tag{4}$$

The most weight matching algorithm can generate a two-molecule graph using the expected value of the node and the matching edge weights. And then it finds the maximum match on the two molecule graph. If and only if find the perfect match, it can obtain the best matching nodes expecta-

Algorithm 2 MS-BFS-Pruning-Grafting

Input : A bipartite graph $G(S, E)$.
Output: Updated the maximum matching mate

for *each* $e \in E$ *in parallel* **do**
  visited$[e] \leftarrow 0$, $root[e] \leftarrow -1$, $parent[e] \leftarrow -1$
for *each* $s \in S$ *in parallel* **do**
  $root[s] \leftarrow -1$, $leaf[s] \leftarrow -1$
T $\leftarrow$unmatched S vertices;
for *each* $s \in F$ *in parallel* **do**
  $root[s] \leftarrow s$
repeat
while $T \neq \phi$ **do**
  $R \leftarrow$ unvisited E, $F \leftarrow$ Update pointers and queue;
  if *s is in an active tree* **then**
    ▷leaf[root[s]]$= -1$;
    for *each unvisited neighbor e of s* **do**
      $parent[e] \leftarrow s$, $visited[e] \leftarrow 1$, $root[e] \leftarrow root[s]$ ▷Update pointers and queue;
      if $mate[e] \neq -1$ **then**
        $Q \leftarrow Q \cup \{mate[e]\}$,
        $root\ \{mate[e]\} \leftarrow root[e]$
      else
        $leaf\ \{root[s]\} \leftarrow e$ ▷end of augmenting path
    for *every unmatched vertex* $s_0 \in S$ *in parallel* **do**
      if *an augmenting path P from* s_0 *is found* **then**
        Augment matching by P
    $F \leftarrow Prun - Graft(G, visited, parent, root, leaf, mate)$
until no augmenting path is found in the current phase

tions. And the role of the matching edge weights is to restrict the new side to join, make to join the new edge can always graph matching number, weight and to obtain the biggest increase again at the same time, algorithm for pseudo code is as follows:

The above algorithm can realize the most weight matching of the same kind of sense nodes and events. In some scenarios, however, a composite event around just a lack of awareness of a kind of have to node, in this case, will not be able to form effective sense of the composite events, therefore, the composite event can give up to match to other nodes, so that sense around the node to choose more qualified composite event, in order to obtain the overall regional composite events sense efficiency maximum. As can be seen in Fig. 8, the composite event lacks the perceived node coverage, so it cannot form an effective sense, so it can consider giving up the matching of the sense node. So that you can match and match, and you get the overall perceived efficiency. Therefore, when the algorithm is executed, the first step can be taken to eliminate the above non-effective sense of composite events.

For the more general situation, each composite event dynamically sets its own sense attraction for surrounding

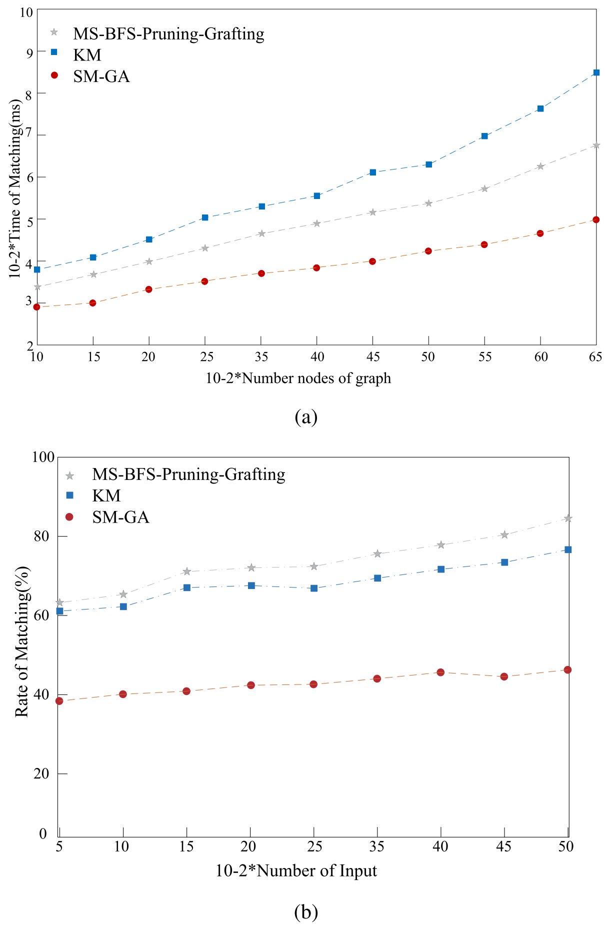


FIGURE 7. algorithm comparison. (a) Run time comparison. (b) Matching rate comparison.

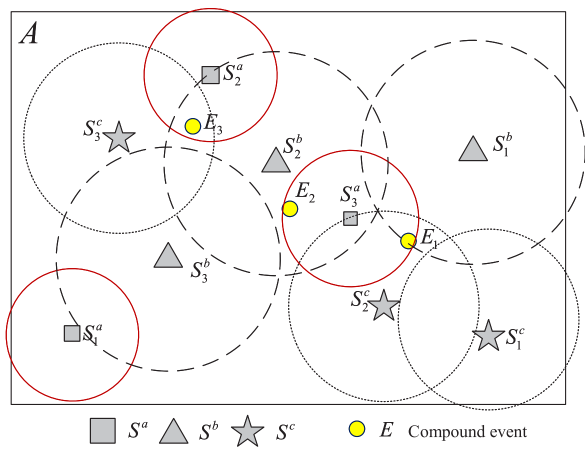


FIGURE 8. Multi-modal sensing nodes' collaborative sense of composite events.

sense nodes based on the situation of the multi-modal sense nodes around itself. Therefore, each composite event E set rewards Ω. Each composite event set different rewards for different kinds of sensing nodes according to the distribution of all kinds of multi-modal sense nodes. In general, for less

Algorithm 3 Maximum Weight Matching Algorithm (MWMA)

Input : Bipartite graph: **G(X, Y)**, Binary matrix: $W\left(x_i, y_j\right)$;
Output: Maximum weight binary matching $M\left(S, T\right)$
Let $S = \emptyset, T = \emptyset$ in $M\left(S, T\right)$;
Initialize the expected value of each element in the set X, Y.
for $Q\left(x_i\right) = \max\left(w_{ig}\right)$ *in X* **do**
  for $Q\left(y_j\right) = 0$ *in Y* **do**
    Loop
    for $x_0 \rightarrow x_m$ **do**
      Search for an augmented path x_iy_j used MS-BFS-Pruning-Grafting
      x_iy_j meet $w_{ij} = \max\left[w_{ig}\right]$, where $y_j \notin T$;
      used x_iy_j augmented M;
      $S \leftarrow x_i, T \leftarrow y_j$;
    if *failed to find an augmented path,* **then**
      Change X, Y set expectation weight $Q\left(x_i\right), Q\left(y_i\right)$;
      Calculated $\Delta = \min\left\{Q\left(x_i\right) + Q\left(y_j\right) - w_{ij}\right\}$;
    for $x_i \in S$*:* $Q\left(x_i\right) = Q\left(x_i\right) - \Delta$*;* **do**
      for $y_j \in T$*:* $Q\left(y_j\right) = Q\left(y_j\right) - \Delta$*;* **do**
        Jump Step 7;
  if *there is no M-Exposure Vertices in X;* **then**
    Return maximum weight matching M, and Stop;
  else
    Return 6;
END

surrounding, more remote sensing nodes are configured with higher returns. In this way, it can achieve the collaborative sense by attracting the sense nodes, so as to maximize the sense efficiency. At the same time, the composite event reward is set to 0, if there is no certain class sense node around itself that cannot form effective cooperative sense. This maximizes the sense effectiveness of the overall composite event by optimizing the maximum weight value matching.

Based on the above ideas, a Smart Matching Algorithm for Collaborative Sense Optimization of Composite Events (CSSMA) is proposed. The pseudocode is as follows: Through the above algorithm, the composite event weighted allocation of multi-modal sensing nodes can be obtained, so that the sense efficiency of the whole event area should be better.

E. THEORETICAL ANALYSIS OF ALGORITHMS

Theorem 1: Algorithm 2 finds a maximum cardinality matching in a bipartite graph $G\left(X \cup Y\right)$.

Proof: If M is the final matching, it returned by the MS-BFS-Pruning-Grafting algorithm. To contradiction, assume that M is not a maximum cardinality matching. According to Berge's theorem, there is another M-augmenting path in the graph. There is an M-augmenting path $P = (x_0, y_0, x_1, \ldots, y_k, x_{k+1}, y_{k+1})$ in the graph. x_0 is the root of an active tree. y_{k+1} is an unvisited vertex. P as a M-augmenting path include at least one edge with an active vertex and an unvisited vertex. According to Pruning-Grafting mechanism, no edge between active and unvisited vertices, the path P does not exist. So M is a maximum cardinality match. □

Algorithm 4 Weighted Allocation of Composite Events Based on Multimodal Sensing Nodes

Input : Bipartite graph: **G(X, Y)**, Match **M**;
Output: Maximum sense efficiency matching **M'**;
Set $M' = M, G' = G$;
for $e_0 \rightarrow e_m$ **do**
  e_i search the peripheral sense nodes set S_i^R based on the composite event composite rules,
if *Various sense nodes e_i in S_i^R;* **then**
  Assign rewards Ω based on the number of different sensors, get $Q\left(y_j\right)$
else
  $\Omega = 0$;
Get bipartite graph $G(X, Y)$ and binary matrix $W\left(x_i, y_j\right)$;
Run the most weight binary matching algorithm MWMA;
END

In this section, the simulations are conducted to evaluate the performance of proposed method.

V. SIMULATION AND RESULTS

A. SIMULATION ENVIRONMENT

In order to verify the performance of the algorithm proposed in this paper, we use MATLAB7.0 as the simulation platform to experiment and analyze this algorithm. The computer configuration is: 8GB of memory, Intel(R) Core^{TM}i7 CPU processor. The simulation experiment is assumed that there are three kinds of sensing nodes to randomize in the area of 120*160m^2. And the combination rules of composite events require the realization of three kinds of perceptual modes. All kinds of sensing nodes and composite events are randomly distributed in the monitoring area. The comparison algorithm includes CSSMA, which proposes under this paper, GA, maximum matching MMA, maximum weight value matching MWMA and other total 4 algorithms. Evaluation indexes mainly include sense efficiency, running time, maximum matching number and other horizontal and vertical comparisons. The algorithm scenario sets three types, as showed in Table 1.

B. PERFORMANCE EVALUATION

First of all, we compare the different sense energy efficiency and running time of the four algorithms in scenario 1,2,3. As showed in Fig. 9, in the three types of scenarios, the algorithm presented in this paper is the most efficient and superior to the other three algorithms. MWMA pursued by the weight

TABLE 1. Settings for different scenarios.

scenario 1		*scenario 2*		*scenario 3*	
Type	*Number*	*Type*	*Number*	*Type*	*Number*
S_A	30	S_A	40	S_A	50
S_B	45	S_B	60	S_B	75
S_C	60	S_C	75	S_C	90
E	12	E	12	E	15

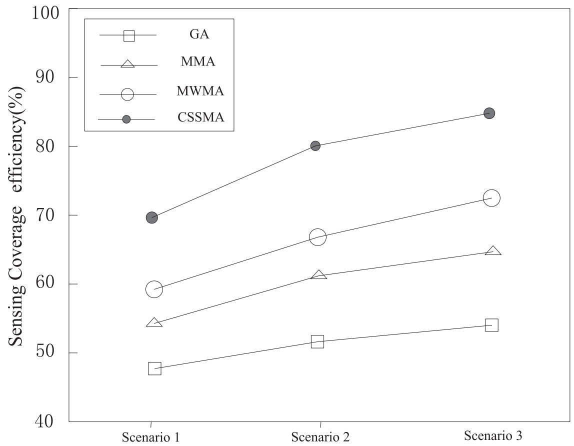


FIGURE 9. The sense performance of the algorithm in different scenes.

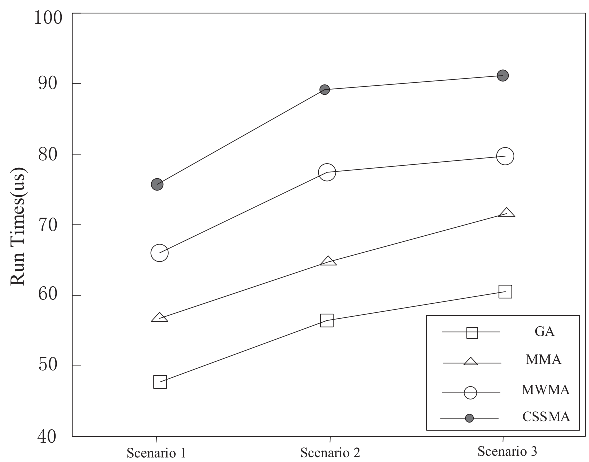


FIGURE 10. Compares the running time of the algorithm in different scenarios.

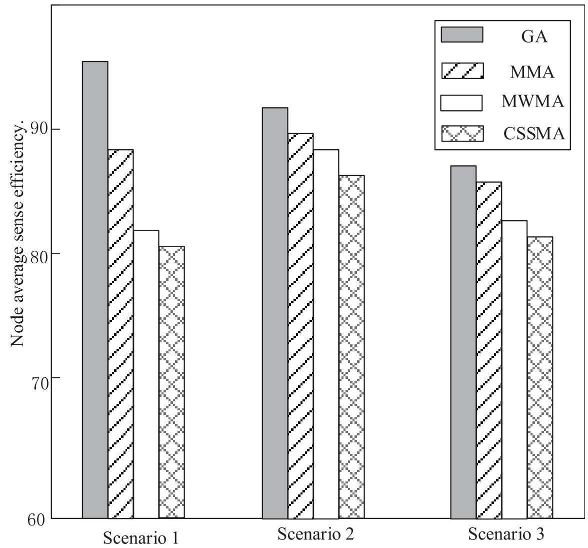


FIGURE 11. Average sense efficiency of each nodes under different scenarios.

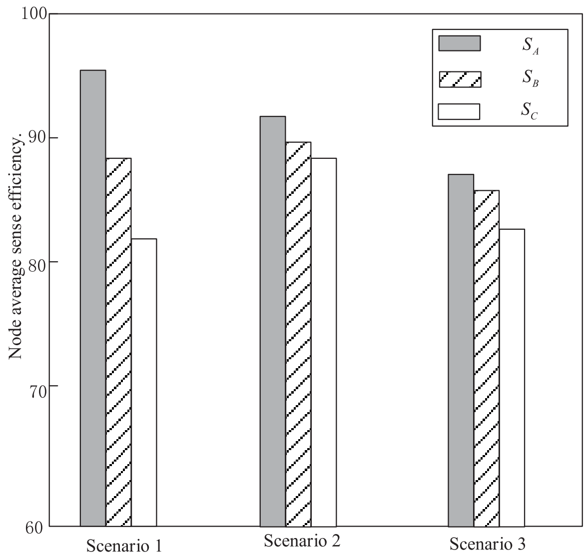


FIGURE 12. The average sense efficiency of CSSMA in different scenarios.

matching algorithm, and then the MMA maximum matching algorithm. Efficiency of algorithms based on the overall sense greedy strategy is the most weak. It main reason for the lack of co-ordination, a single node largest sense quality can't ensure the quality of the overall maximization. However, the algorithm proposed in this paper is coordinated with the composite event sense of multi-modal sensing node.

The running time of the four algorithms is presented in Fig. 10. GA based on a greedy strategy has the shortest running time. And the algorithm itself determines that each sensor node always finds the nearest composite event around itself. The algorithm process is simple. GA is based on the strategy of maximizing matching, so the search speed is fast, while the performance is not as good as other algorithms. MMA and MWMA consider the distance weight and the coordination of overall performance respectively, so their execution process is more complex and the running time is longer. In the following analysis, in different scenarios, the average perceived energy efficiency comparison of each algorithm's individual sense nodes is compared, and the simulation results are shown in Fig. 11, 12.

It can be observed that the average efficiency of each sensing node of GA algorithm is the most. And it always searches for the latest events around it, so the sensor efficiency is maximized. MMA and MWMA algorithm are lower than GA. Node sense effectiveness of CSSMA algorithm is the

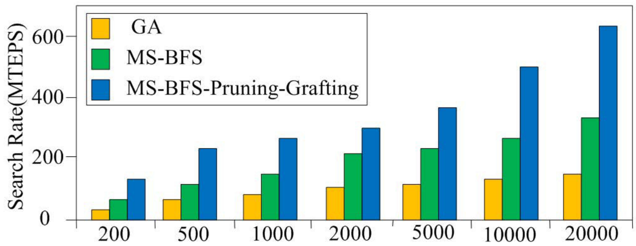


FIGURE 13. Search rate comparison.

TABLE 2. Settings for different scenarios. Number $\times 10^2$.

Number $\times 10^2$

Scenario Graph \ Sensors & Events	S_A	S_B	S_C	E
Scenarios 4	25	50	70	20
Scenarios 5	40	40	40	30
Scenarios 6	70	70	70	50

lowest. At the same time, its overall effectiveness is the best. This shows that the algorithm has better sense collaboration. Unique sense of GA algorithm efficiency is high, and the overall sense of efficiency is low, explain repetition rate is good, so the efficiency is low.

It can be seen that sense an effect on the composite event of three kinds of sensor nodes. In the first and second scenario, the number of composite events is constant and the number of sensor nodes increases. In the second and third scenario, the number of nodes increases and the number of composite events increases. The efficiency of each sensor node is reduced.

For the MS-BFS-Pruning-Grafting algorithm proposed, we compare search rate between different algorithms with traversing edges per second (TEPS). TEPS is determined by the ratio of edges traversed in total runtime. MS-BFS-Pruning-Graft algorithm traverses edges with a faster rate in comparison to MS-BFS and GA. Fig. 13 shows MS-BFS-Pruning-Grafting with excellent search performance. The improvement mainly comes from Pruning-Grafting mechanism and parallel strategy. It is particularly true for our multi-sensor and multi-event scenarios.

Let's analyze this further that the characteristics of the proposed algorithm. It set three scenarios as shown in table 3, and the comparison algorithm includes GA, KM, MWMA and CSSMA. Sense nodes are randomly distributed in the area. We did a number of experiments and then averaged the results. The experiments results are shown in the Figure 14,15,16,17.

For the composite event monitoring, the matching rate of each sensor node to different types of the event is analyzed below. In scenario 4, the number of sensor nodes of different types varies greatly, and the matching rate of different sense nodes for events is different. The matching rate of all sorts of

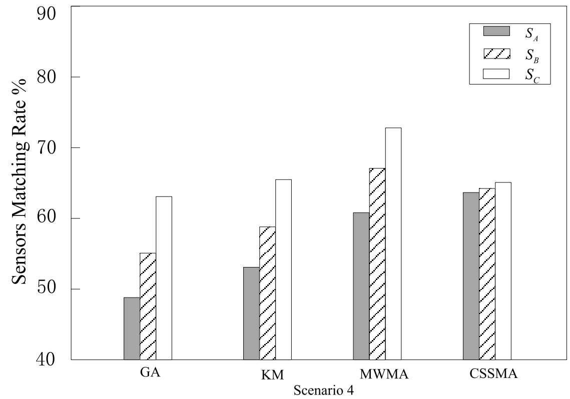


FIGURE 14. Scenario 4 results.

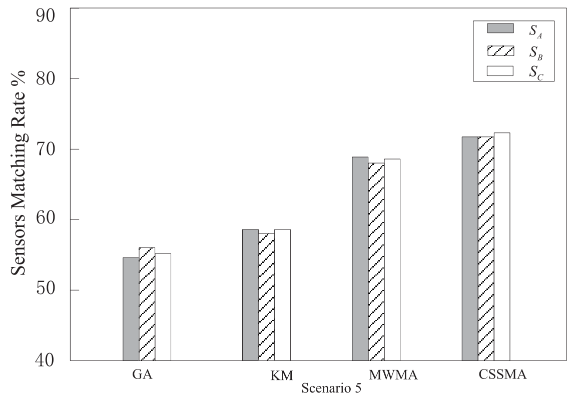


FIGURE 15. Scenario 5 results.

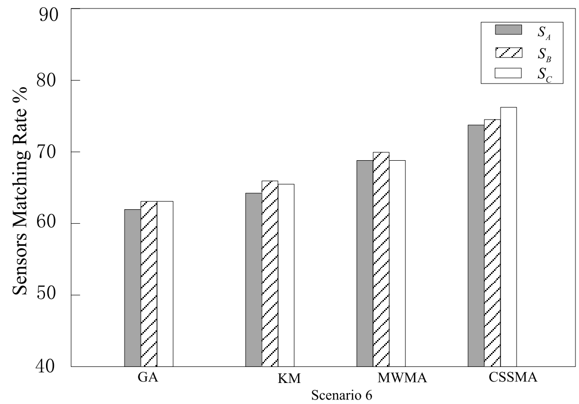


FIGURE 16. Scenario 6 results.

sensors can reach 78% at most and 46% at least. The matching rate gap of different sense nodes in the same algorithm is also different, for example, GA algorithm has the largest matching rate of all kinds of sense nodes. The largest S_A was 46%, S_C 63%, and the gap between them was 17%. As see from the results in Fig. 14-17, GA, KM and MWMA algorithms performance is getting higher and higher. Due to the difference in the number of nodes, there is also a difference in the matching degree. Scenario 5 and 6 is under the condition that

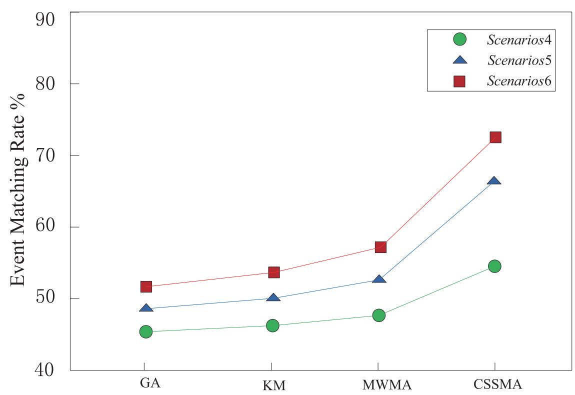


FIGURE 17. Event Matching Rate.

the number of sensors is greater than the number of composite events and the number of sensors is the same. It can be seen from the test results in Fig. 15 that the matching rate of different sensors in the same algorithm is relatively close in Fig. 16. This happens because the number of nodes is the same, so it is only related to the random distribution of sense nodes. Secondly, the matching rate of CSSMA algorithm is lower than that of MWMA, which is due to the local sacrifice to balance the matching of different sensors. And in the overall composite event matching, CSSMA is obviously superior to the other three types of algorithms in Fig. 17. This is also in line with the original intention of the algorithm design, that is, the matching rate of some nodes is sacrificed to maximize the matching rate of the whole event.

VI. CONCLUSIONS

Multimodal sensing nodes have significant applications in the collaborative sense of composite events. Currently, there are relatively few researches on the collaborative sense of composite events, and most of them are transformed into single coverage problems. In order to solve the problem of composite event co-optimization with different sensing nodes, this paper puts forward the most robust matching algorithm based on collaborative sense. Finally by comparing with other algorithms, this algorithm has a certain advantage in the overall sense efficiency, in terms of composite events collaborative sense has good theoretical significance and practical value.

However, in this paper, as a kind of heuristic algorithm approximate performance lack of comparison. The next step of work, it can need to be further analyzed in terms of algorithm theory. And, the collaborative sense of composite events was studied combining with a group of intelligence algorithm.

REFERENCES

[1] M. Zhan, J. Wu, H. Wen, and P. Zhang, ''A novel error correction mechanism for energy-efficient cyber-physical systems in smart building,'' *IEEE Access*, vol. 6, pp. 39037–39045, 2018.

[2] X. Lu, J. Liu, W. Qi, and Q. Dai, ''Multiple-target tracking based on compressed sensing in the Internet of Things,'' *J. Netw. Comput. Appl.*, vol. 122, pp. 16–23, Nov. 2018.

[3] A. Quarto *et al.*, ''IoT and CPS applications based on wearable devices. A case study: Monitoring of elderly and infirm patients,'' in *Proc. IEEE Workshop Environ., Energy, Struct. Monit. Syst.*, Jul. 2017, pp. 1–6.

[4] X. Lu, R. Chen, J. Liu, and L. Cheng, ''Square partition-based node scheduling algorithm for wireless passive sensor networks,'' *Int. J. Commun. Syst.*, vol. 31, no. 8, p. e3531, 2018.

[5] D. A. Chekired, L. Khoukhi, and H. T. Mouftah, ''Industrial IoT data scheduling based on hierarchical fog computing: A key for enabling smart factory,'' *IEEE Trans. Ind. Inform.*, vol. 14, no. 10, pp. 4590–4602, Oct. 2018. doi: 10.1109/TII.2018.2843802.

[6] A. K. Sangaiah, D. V. Medhane, T. Han, M. S. Hossain, and G. Muhammad, ''Enforcing position-based confidentiality with machine learning paradigm through mobile edge computing in real-time industrial informatics,'' *IEEE Trans. Ind. Inform.*, to be published. doi: 10.1109/TII.2019.2898174.

[7] J. C. C. Tseng, J. Gu, P. F. Wang, C. Chen, C. Li, and V. S. Tseng, ''A scalable complex event analytical system with incremental episode mining over data streams,'' in *Proc. IEEE Congr. Evol. Comput.*, Jul. 2016, pp. 648–655.

[8] W. Wu, S. Pirbhulal, A. K. Sangaiah, S. C. Mukhopadhyay, and G. Li, ''Optimization of signal quality over comfortability of textile electrodes for ECG monitoring in fog computing based medical applications,'' *Future Gener. Comput. Sci.*, vol. 86, pp. 515–526, Sep. 2018.

[9] X. Dong, ''Deployment cost optimal for composite event detection in heterogeneous wireless sensor networks,'' in *Proc. 3rd Int. Conf. Inf. Sci. Control Eng. (ICISCE)*, Beijing, China, Jul. 2016, 1288–1292.

[10] A. Mtawa, H. S. Hassanein, and N. Nasser, ''Identifying bounds on sensing coverage holes in IoT deployments,'' in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, San Diego, CA, USA, Dec. 2015, pp. 1–6.

[11] Y. Cheng, S. Zhao, B. Cheng, S. Hou, X. Zhang, and J. Chen, ''A distributed event-centric collaborative workflows development system for IoT application,'' in *Proc. IEEE 37th Int. Conf. Distrib. Comput. Syst. (ICDCS)*, Atlanta, GA, USA, Jun. 2017, pp. 2547–2550. doi: 10.1109/ICDCS.2017.99.

[12] M. Rescati, M. De Matteis, M. Paganoni, D. Pau, R. Schettini, and A. Baschirotto, ''Event-driven cooperative-based Internet-of-Things (IoT) system,'' in *Proc. Int. Conf. IC Des. Technol. (ICICDT)*, Otranto, Italy, Jun. 2018, pp. 193–196. doi: 10.1109/ICICDT.2018.8399789.

[13] A. Alagha, S. Singh, R. Mizouni, A. Ouali, and H. Otrok, ''Data-driven dynamic active node selection for event localization in IoT applications—A case study of radiation localization,'' *IEEE Access*, vol. 7, pp. 16168–16183, 2019. doi: 10.1109/ACCESS.2019.2894956.

[14] J. Gao, J. Li, Z. Cai, and H. Gao, ''Composite event coverage in wireless sensor networks with heterogeneous sensors,'' in *Proc. IEEE 34th Conf. Comput. Commun. (INFOCOM)*, Apr./May 2015, pp. 217–225.

[15] K. Takazawa, ''Finding a maximum 2-matching excluding prescribed cycles in bipartite graphs,'' *Discrete Optim.*, vol. 26, pp. 26–40, Nov. 2017.

[16] H. Chen and H. Deng, ''Extremal bipartite graphs of given connectivity with respect to matching energy,'' *Discrete Appl. Math.*, vol. 239, pp. 200–205, Apr. 2018.

[17] J. Han, D. Zhang, G. Cheng, L. Guo, and J. Ren, ''Object detection in optical remote sensing images based on weakly supervised learning and high-level feature learning,'' *IEEE Trans. Geosci. Remote Sens.*, vol. 53, no. 6, pp. 3325–3337, Jun. 2015.

[18] T. Öncan and I. K. Altinel, ''A branch-and-bound algorithm for the minimum cost bipartite perfect matching problem with conflict pair constraints,'' *Electron. Notes Discrete Math.*, vol. 64, pp. 5–14, Feb. 2018.

[19] S. Aslan and M. Kaya, ''Link prediction methods in bipartite networks,'' in *Proc. Int. Conf. Comput. Sci. Eng. (UBMK)*, Antalya, Turkey, Oct. 2017, pp. 1095–1099.

[20] Y. Cai, S. Liu, J. Hu, G. Bai, and S. Dong, ''A hybrid bipartite graph based recommendation algorithm for mobile games,'' in *Proc. IEEE Int. Conf. Big Data (Big Data)*, Boston, MA, USA, Dec. 2017, pp. 3575–3582.

[21] X. He, M. Gao, M.-Y. Kan, and D. Wang, ''Birank: Towards ranking on bipartite graphs,'' *IEEE Trans. Knowl. Data Eng.*, vol. 29, no. 1, pp. 57–71, Jan. 2017.

[22] D. Bokal, B. Brešar, and J. Jerebic, ''A generalization of Hungarian method and Hall's theorem with applications in wireless sensor networks,'' *Discrete Appl. Math.*, vol. 160, nos. 4–5, pp. 460–470, 2012.

[23] J. Langguth, A. Azad, M. Halappanavar, and F. Manne, ''On parallel push–relabel based algorithms for bipartite maximum matching,'' *Parallel Comput.*, vol. 40, pp. 289–308, Jul. 2014.

[24] B. Chen, M. Lei, and M. Zhao, ''An optimal resource allocation method for multi-user multi-relay DF cognitive radio networks,'' *IEEE Commun. Lett.*, vol. 20, no. 6, pp. 1164–1167, Jun. 2016.

[25] A. Azad, A. Buluç, and A. Pothen, "Computing maximum cardinality matchings in parallel on bipartite graphs via tree-grafting," *IEEE Trans. Parallel Distrib. Syst.*, vol. 28, no. 1, pp. 44–59, Jan. 2017.

[26] A. Azad and A. Buluç, "Distributed-memory algorithms for maximum cardinality matching in bipartite graphs," in *Proc. IPDPS*, May 2016, pp. 32–42.

[27] A. Azad, A. Buluç, and A. Pothen, "A parallel tree grafting algorithm for maximum cardinality matching in bipartite graphs," in *Proc. IEEE Int. Parallel Distrib. Process. Symp.*, May 2015, pp. 1075–1084.

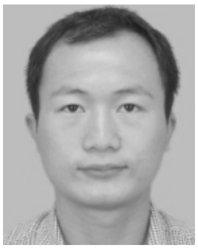
[28] P. Chatterjee, S. C. Ghosh, and N. Das, "Load balanced coverage with graded node deployment in wireless sensor networks," *IEEE Trans. Multi-Scale Comput. Syst.*, vol. 3, no. 2, pp. 100–112, Apr./Jun. 2017.

[29] Q. He, D. Yuan, and A. Ephremides, "Maximum link activation with cooperative transmission and interference cancellation in wireless networks," *IEEE Trans. Mobile Comput.*, vol. 16, no. 2, pp. 408–421, Feb. 2017.

[30] I. S. Duff, K. Kaya, and B. Uçcar, "Design, implementation, and analysis of maximum transversal algorithms," *ACM Trans. Math. Softw.*, vol. 38, no. 2, pp. 13:1–13:31, 2011.

[31] A. Azad, M. Halappanavar, S. Rajamanickam, E. G. Boman, A. Khan, and A. Pothen, "Multithreaded algorithms for maximum matching in bipartite graphs," in *Proc. IEEE 29th Int. Parallel Distrib. Process. Symp.*, May 2012, pp. 860–872.

[32] T. A. Davis and Y. Hu, "The university of florida sparse matrix collection," *ACM Trans. Math. Softw.*, vol. 38, no. 1, p. 1, 2011.



JUN LIU received the M.S. degree in control science and engineering and the Ph.D. degree from the Guangdong University of Technology, Guangzhou, China, in 2012, and 2015, respectively. He is currently a Lecturer with the School of Automation, Guangdong Polytechnic Normal University. His current research interests include the Internet of Things, big data, and machine learning.

FEI YUAN received the Ph.D. degree in control theory and control engineering from Sun Yat-sen University, China, in 2014. He is currently a Lecturer with the School of Automation, Guangdong Polytechnic Normal University, China. His research interests include the Internet of Things and wireless sensor networks.

JIANHUA WANG was born in Guangdong, China, in 1982. He received the B.S degree in electronic information science and technology from Shaoguan University, Guangdong, China, in 2006, and the Ph.D. degree in control science and engineering from the Guangdong University of Technology, Guangdong, China, in 2015. He is currently a Teacher with the College of Electronic Engineering, South China Agricultural University, Guangzhou, China. His research interests include video signal processing and massive data processing in the IoT.

XU LU received the M.S. and Ph.D. degrees in control theory and control engineering from the Guangdong University of Technology, China, in 2009 and 2015, respectively. He is currently an Associate Professor with the School of Computer Science, Guangdong Polytechnic Normal University, China. His research interests include the Internet of things and wireless sensor networks.