Structural X-ray Image Segmentation for Threat Detection by Attribute Relational Graph Matching

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Abstract—**This paper addresses part of the problem dealing with the automatic threat detection for accompanied baggage based on multi-energy X-ray imagery for Station Security. Segmentation is the first significant stage to extract interested objects in the images for detailed analysis and recognition at following stages. In order to obtain the integrated objects for subsequent analysis and recognition, we propose a structural segmentation method based on ARG matching. The proposed segmentation algorithms are a series of graph-matching algorithms based on models under a kind of similarity measure, fuzzy similarity distance (FSD) that represents the similarity of the attributed relation between the vertex neighborhood and a certain model. Finally, the Number of Layer attribute for each region is obtained, and the integrated objects can be extracted using relational attributes and space information. The results show a good average integrity of objects segmented from experimental images.**

I. INTRODUCTION

Threat detection for the purposes of station security is an important area in public traffic security [1]. For the purposes of rail traffic security in our country, safety check is usually performed on imagery of carry-on baggage of passengers based on multi-energy x-ray imaging technology. In our automated detection system, objects of interest are extracted from baggage x-ray imagery, some features of them are then used to characterize the resulting objects, and finally, those with suspicion are marked so that human screeners can get alert and easily detect them.

Image segmentation is the first significant part of this detection system. Before any object can be labeled as suspicious one, it must be isolated from all others. A number of methods have been proposed for aviation security detection [2-5], and the segmentation algorithms employed segment an image into non-overlapping suspicious regions. However, due to complexity of articles in passenger baggage, the X-ray images generally contain regions in which different objects are overlapped. Thus, by traditional non-overlapping segmentation method, overlapped objects are segmented into different parts in all probability, while overlapping regions are sometimes segmented as single objects. Based on these segments, feature extraction and object recognition usually result in undesirable outputs. In order to obtain the integrated objects, overlapping regions should be multi-segmented and allocated to different objects simultaneously.

In this paper, we propose a structural segmentation method based on attributed relational graphs (ARGs), which are usually employed for object representation in structural pattern recognition [6]. An x-ray image is firstly represented by an ARG, after it has been segmented into homogeneous non-overlapping parts using low-level segmentation techniques according to color and texture features. Then the most matching model for every neighborhood subgraph of the ARG should be picked out from Neighborhood Structure Model Base (NSMB) designed in advance, and for each region a special attribute – *Number of Layers* (NL), defined for describing how many objects overlap in the region, is calculated according to the matching result. Finally, when the NL attributes of all the regions in the image have been obtained, the integrated objects in the image can be extracted using region attributes and model information.

ARG matching of subgraphs of an image and a model is one of the most important problems in the segmentation method. ARG matching problem was proved to be NP-hard, so various heuristic algorithms have been developed to improve the efficiency. In this paper, using fuzzy similarity distance (FSD) for matching measure, we design matching algorithms for each model in NSMB according to their special structures, considering that the neighborhood subgraphs of the models are with small size, usually no more than 10 vertices and they are parametric models changed with matching result. These algorithms can be executed in parallel, and finally most matched model would be found.

The rest of the paper is organized as follows. In Section II, we describe the ARG expression used in this paper and propose the ARG representation for images and models. A brief introduction of the segmentation algorithm is presented in Section III. Section IV is devoted to the evaluation functions for the problem and the design of the matching algorithms. Experimental results are given in Section V and we conclude this paper in Section VI.

II. ARG REPRESENTATION

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ARG is a kind of weighted graph of relation and comes from mark sheet. The definition of ARG used in this paper directly comes from [7].

Definition: Formally, an ARG is defined as

$$G=\{V,E,R^{(1)},R^{(2)}\} \tag{1}$$

where $V=\{v_1,v_2,\cdots,v_n\}$ represent the n vertices of the graph and these vertices are correspond to pixels, lines, curves or regions in the image; $E=\{e(i,j)\mid v_i,v_j\in V\}$ is the set of edges between different vertices; $R^{(1)}=\{\boldsymbol{r}^{(1)}(i)\mid v_i\in V\}$ is the attribute set of vertices and $\boldsymbol{r}^{(1)}(i)$ is an N-dimension vector which represents N different attributes of vertex v_i; $R^{(2)}=\{\boldsymbol{r}^{(2)}(i,j)\mid e(i,j)\in E\}$ is the attribute set of weighted edges, and $\boldsymbol{r}^{(2)}(i,j)$ is an M-dimension vector which represents M different attributes of edge $e(i,j)$.

In this paper, we denote the ARGs of an image as $G^S=\{V^S,E^S,R^{S(1)},R^{S(2)}\}$, and that of a model as $G^M=\{V^M,E^M,R^{M(1)},R^{M(2)}\}$.

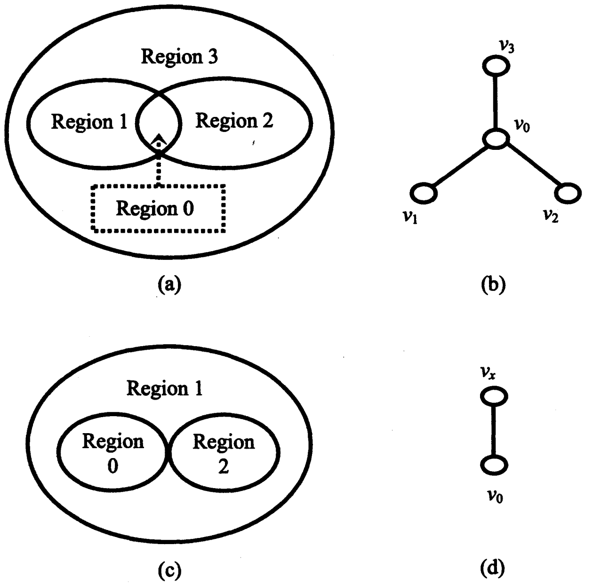


Fig. 1. Two Models in NSMB; (a) a sketch map for a *one-to-one* model; (b) the brief ARG of the *one-to-one* model; (c) one of sketch maps for a *one-to-multiple* model; (d) the brief ARG of the *one-to-multiple* model

A. ARG Representation

In this subsection, we describe the ARG representation used in our work. Vertices correspond to regions and edges correspond to relationships between regions. The set of edges includes only those between adjacent regions. Both vertices and edges are labeled by the attribute values of the region properties and the relationship properties, respectively. In this work, we use the following set of features: (detailed description of these attributes can be found in [9])

1) *Vertex Attributes:* Individual regions are described by three attributes, namely *Perimeter* (p), computed as the perimeter of the area of a region, *Luminance* (l), computed as the dominant average luminance of a region, and *NL* (n), defined as number of objects overlap in a region and initialized by the value 0.

2) *Edge Attributes:* Spatial relationships between regions are described by four attributes, namely *Border Length* (b), computed as the length of the border between two regions, *Relative Angle* (a), defined as the angle with the horizontal direction of the line connecting the centers of mass of the two regions, *Relative Position* (o), defined as one of the three positions: *inner*, *outer* and *side-by-side*, and *Conjoint Border Relative Flatness* (f), computed as degree of border flatness at the joints of borders of adjacent two regions.

TABLE I

DETAILED DESCRIPTION OF ATTRIBUTES OF FIG1(b) MODEL

(i) Vertex Attributes

v \ $\boldsymbol{r}^{(1)}$	l	p
v_0	$(l_0)=l_1*l_2/l_3$	(p_0)
v_1	(l_1)	(p_1)
v_2	(l_2)	(p_2)
v_3	$(l_3)>l_1$ $(l_3)>l_2$	(p_3)

(ii) Edge Attributes

e \ $\boldsymbol{r}^{(2)}$	b	a	o	f
$e(0,1)$	(b_{01}) $\geq p_0/2$	$(a_{01})=(a_{02}+180°)$ mode 360°	*side-by-side*	(f_{01}) ≥ 0.5
$e(0,2)$	(b_{01}) $\leq p_0/2$	$(a_{02})=(a_{01}+180°)$ mode 360°	*side-by-side*	(f_{02}) ≥ 0.5
$e(0,3)$	(b_{01}) ≤ 5	(a_{03})	*inner*	(f_{03})

B. Models in NSMB

By examining experimental images, various neighborhood structure ARG models of overlapping and non-overlapping regions have been built. These models represent abstract structures of regions and their neighborhood, and they are divided into two styles according to vertex type: *one-to-one* that implies one vertex in model corresponding to one region in image and *one-to-multiple* that implies one vertex corresponding to more than one region. Each model has a center vertex (default denoted as v_0) that represents the center region (default denoted as Region 0) and some side vertices that represent its neighbor regions. In our work, only the relationships between each side vertex and the center vertex are defined as edges of model. Considering the simpleness of model expression and matching method, we do not use the relations between two side vertices. Fig.1a and Fig.1c show sketch maps of a simple example for *one-to-one* model and a simple example for *one-to-multiple* model, and the brief ARG of the two models are shown in Fig.1b and Fig.1d.Image ARG is generated from true value of regions, while model ARG is represented by variables and formulas consisted with these variables and constant (see Table I). In the table, the variables, denoted as (p_0) etc., represent the related attributes of certain vertices or edges, and when there is no formula for the attributes, it means that they are free from restriction and can be evaluated with arbitrary values. NL attribute is not included in the expression of model for matching algorithm, because it could not be used in this phase and would be calculated when all matching models have been found.

III. SEGMENTATION ALGORITHM

The proposed segmentation strategy consists of two phases. In the pre-segmentation phase, an X-ray image is segmented into non-overlapping segments; and ARG matching method is applied to subgraphs of the pre-segmented image represented by ARGs and the models in the post-segmentation phase to define the NL values of vertices (regions). After the NL attributes are all obtained, the image ARG is completed and the integrated objects in image can be extracted.

A. Pre-segmentation

In the pre-segmentation phase, a region is defined as a homogeneous group of connected pixels with respect to color and texture features. We pre-segment the image using the revised algorithm proposed in [8]. Considering the noisy x-ray images, the mean value of the Hue component of a given region is not obtained from the whole region, but from analyzing H-histogram of the region and calculating the mean value in the interval which contains the most distinctive peak and more than 80% pixels with the least interval width. When the iterative merging process has been finished, a marked matrix that labels the pre-segmented regions can be obtained.

B. Models in NSMB

After an input color image has been pre-segmented and represented by ARG, ARG matching is adopted to calculate the special region attribute, NL, which is not determined until matching operations have been imposed on all regions. First, the vertices in ARG obtained in the pre-segmentation phase are sorted according to the possibilities for them to be the overlapping ones. Secondly, the neighborhood of each vertex is matched against the stored models in parallel by special matching algorithms designed for each model. Finally, the best matching model is picked out for identifying the most probable neighborhood structure. We propose a kind of fuzzy similarity distance (FSD) that represents the similarity of the attributed relation between the vertex neighborhood and a certain model. FSD is calculated by a fuzzy membership grade function. Based on prior knowledge, a series of models are built to represent the potential neighborhood structures of regions and these models compose the NSMB. In the NSMB, 38 different models, 16 *one-to-multiple* models and 22 *one-to-one* models, have been included, which are extracted from the examined example images and have similar appearances with the models showed in Fig.1 and Table I. However, these models may be inadequate for practical application, thus an alert mechanism is adopted in our system to find out new models and expand the model base. The alert mechanism is as follow: a threshold selected by experience is used to determine whether the shortest fuzzy similarity distance is short enough for a region neighborhood to belong to a model; if a region probably matches no model, a special mark is set for the region. Unseen structures of regions are recorded and should be manually processed later.

C. NL Setting and Objects Extraction

Each region in image has a model mark or a special one now, so the last work is to determine the NL attribute. We can simply set out from the brightest region, which obviously is a region belonging to the first layer. Process continues; each region picked out to be dealt with is the brightest region of the adjacent regions of all regions that have been processed. When a region is selected, its NL value should be determined according to the corresponding model and the NL value of other regions with determined layer number. If meet a special mark, the region layer value are evaluated to be the value same to its neighbor region whose luminance is closest to it.

After NL value of each region is obtained, we finish the post-segmentation stage by determining integrated objects according the layers and models to which regions belong. Three principles are proposed for objects determination: (1) The first layer in the image should be considered as background, so the regions have the layer number of 1 are not belong to any object; (2) If a region of higher layer has a neighbor of lower layer and they become flatter at the point of intersecting when combined together (this can be decided by the models they belong to), the two regions are contained in the same object; (3) A region with layer number k belongs to adjacent layer k-1 objects simultaneously.

IV. ARG MATCHING ALGORITHM

Due to the special parametric models proposed in Section II, it is very hard to naturally introduce conventional heuristic optimization algorithms into our work. In [9], we had described a serial algorithm to deal with the whole ARG-matching problem. However, the NP-hard property of ARG matching problem requires a kind of optimized algorithm to ensure the reasonable time complexity. In order to make full use of the information contained in the models and improve the efficiency of the matching process, a series of matching algorithms are designed in this paper according to the special structure of corresponding models respectively, that is to say, there are 38 different algorithms in the system and each algorithm corresponds to a certain model. A selected scene subgraph is processed by these programs in parallel, FSD value and corresponding arrangement of the scene and the model are the output results of these programs, and the model with minimum FSD value is the most matched model for the scene.

A. Fuzzy Similarity Distance (FSD)

Measuring similarity distance between two graphs is one of the most significant tasks on graph isomorphism and graph matching. Taking the special models we adopt into account, we define FSD measure.

With the expression defined in Section II, image scene and model ARGs are respectively denoted as $G_S = \{V_S, E_S, R_S^{(1)}, R_S^{(2)}\}$ and $G_M = \{V_M, E_M, R_M^{(2)}, R_M^{(2)}\}$. $|V_x|$ and $|E_x|$ represents the number of vertices of G_x and that of edges of E_x, equal to n_x+1 and n_x respectively. v_0^x corresponds to the center region of the graph; $r_x^{(1)}(i)$ is a 3-dimension vector which represents 2 different attributes of vertex v_i^x: *l* and *p*, and $r_x^{(2)}(i,j)$ is an 4-dimension vector which represents 4 different attributes of edge $e^x(i,j)$: *b*, *a*, *o*, *f* (see Section II).

Before the FSD of G_S and G_M are calculated, the values of vertex and edge attributes of G_S should be evaluated to G_M first. Let $G_S(t)$ be an arrangement of G_S at time *t*, then the values in $G_S(t)$ are evaluated to G_M and $G_M(t)$ is obtained. The FSD of G_S and G_M at time *t* is defined as follow:

$$\mathrm{FSD}(G_S, G_M) = \sum_{k=1}^{n_x+1}\sum_{i=1}^{2} w^{v^i}(1 - fmg_{G_M(t)}^{(v^i)}(k)) + \sum_{k=1}^{n_x}\sum_{i=1}^{4} w^{e^i}(1 - fmg_{G_M(t)}^{(e^i)}(k)) + n_r \tag{2}$$

where v^i and e^i represent the *i*th attribute of vertex and edge respectively, $fmg_{G_M(t)}^{(*)}(k))$ is the fuzzy membership grade of v_k or $e(0,k)$ on certain attribute, w^* is the related weight that represent the importance of an attribute, and n_r is the number of vertices that cannot find pair in model *M*. There are several fuzzy relationships should be evaluated, including >, <, =, ≤, ≥, and their combinations, such as <…<, etc. We take the relationship ≤ as example to describe the evaluation of $fmg_{G_M(t)}^{(*)}(k))$. Let the relationship be $r_M^{i(*)} \le C$, then

$$fmg_{G_M(t)}^{(*)}(k)) = \begin{cases} 1 & r_{Mk}^{i(*)} \le C \\ 1 - \dfrac{r_{Mk}^{i(*)} - C}{d_i} & C < r_{Mk}^{i(*)} \le C + d_i \\ 0 & r_{Mk}^{i(*)} > C + d_i \end{cases} \tag{3}$$

where d_i >0 is the selected effective similar distance for the attribute *i*. Other relationship types have the nearly same formulas to (3).

B. ARG Matching Algorithms

According to the FSD functions and model structures we can design a set of algorithms corresponding to the models. The rules for design of the algorithms include: (1) Due to determination of center vertex, the variables related to v_0^M are determined first; (2) The side vertices are classified according to the attributes formulas that have distinct or contrary evaluation for different class of vertices; (3) Side vertices belonging to the same class should attempt all possible arrangement to search the most matching status, and the number of vertices to be arranged in this phase is usually very small, no more than 4.

There are two model types and 38 models in NSMB. In this section, we present only two algorithms that correspond to the simple models expressed in Fig.1 for representation, and other algorithms are designed similarly. Table II describes the algorithm for the one-to-one model (OTO-10 in NSMB) showed in Fig.1a, and Table III for the one-to-multiple model (OTM-1 in NSMB) showed in Fig.1c.

TABLE II

FSD-BASED OTO-10 MODEL ALGORITHM

Input: G_S (3~5 vertices)
Output: Mapping from G_S to G_M and FSD value

A. Initialization
a. Attributes of v_0 in G_M are evaluated according to v_0 in G_S
b. All v_0 variables in formulas for G_M are evaluated

B. Side Vertices Classification
a. Pick out the side vertex that has the maximum *l* value and whose edge with v_0 has the '*inner*' value on attribute *o*; the vertex is determined to be v_3
b. Other vertices are put together to form a class (1~3 vertices)

C. Side Vertices Matching By Class
a. Arrange side vertices of the class to obtain pairs and correspondingly revise the attributes
b. Calculate the FSD under current arrangement and record it
c. Determine whether there is any untried arrangement; if there is, go to *a.*
d. Record the minimum of FSDs as the FSD between the scene and the model, and the corresponding arrangement as the most matching mapping

TABLE III

FSD-BASED OTM-1 MODEL ALGORITHM

Input: G_S
Output: Mapping from G_S *to* G_M and FSD value

A. Initialization
a. Attributes of v_0 in G_M are evaluated according to v_0 in G_S
b. All v_0 variables in formulas for G_M are evaluated

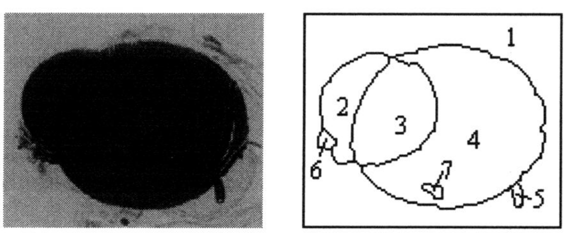
B. Side Vertices Matching
a. Side vertices are all matched to v_x in the model.
b. Calculate the FSD under this matching
d. Output the FSD result and the mapping

B. ARG Matching in Parallel

Owing to the independence of different models, the matching process can be done in parallel. When a subgraph of a scene is selected into the process, all possible models are to be picked out for matching according to the model structure. Matching processes are done in parallel, and when the results have been obtained, the model with the minimum FSD is chose to be the matching one. A threshold T is defined in advance, and if the minimum is larger than it, unmatching should be declared.

V. EXPERIMENT RESULT

We used a total of 60 x-ray images gathered from Nanchang railway station all of which contain illicit articles. Single packages in these images were first selected to present to pre-segmentation module. Due to the special application, we took statistics on luminance of illicit articles and determined a threshold L, first. Those neighbor regions, that have a luminance value beyond L, were merged in pre-segmentation stage, even though they had not been merged during the course of pre-segmentation. An example of experimental original image and its sketch map of pre-segmented result are shown in Fig.2.



(a) (b)

Fig. 2. An experimental example; (a) original image; (b) sketch map of pre-segmentation result

Further processing was performed on the pre-segmented images. Fig.3 is the brief ARG representation of the segmented regions of the image showed in Fig.2b. Each ARG vertex and its neighborhood consisted of its neighbor regions were matched to the models in NSMB, and the results for this experiment are shown in Table IV. In our experiments, the threshold T for FSD was set to be 1.6, and w^* ranged from 0.2 to 0.5.

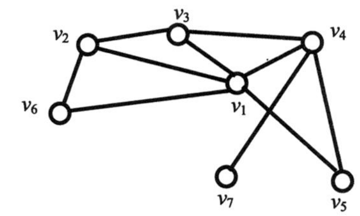


Fig.3. ARG representation of Fig.2b

TABLE IV

MODEL MATCHING RESULTS OF ARG IN FIG.3

Center Region	Model	Min FSD	Layer	True Layer
V1	OTM-1	0	1	1
V2	OTM-2	0.37	2	2
V3	OTO-10	0.51	3	3
V4	OTM-2	0.26	2	2
V5	OTM-7	0.18	2	2
V6	OTM-8	0.22	2	2
V7	OTO-2	0	3	3

TABLE V

OBJECTS EXTRACTED

Object	Compositive Regions
1	{1, 2, 3, 4, 5, 6, 7}
2	{3, 4, 7}
3	{2, 3}
4	{6}
5	{5}
6	{7}

When the final layers of all regions had been determined, we extracted objects from the image according to the models and the layer number of regions. The objects obtained for the example image are showed in TABLE V. We find that the segmented result of two overlapping objects in the backpack is more integrated than we can expect from traditional segmentation methods, although not completely integrated (being compared with the objects extracted manually).

VI. CONCLUSIONS

In this paper we have developed a structural segmentation method using parallel ARG matching for overlapping objects segmentation in x-ray images, which can be applied to the station security application. The integrated object extraction is one of the most difficult tasks in image segmentation. Our ideas come from structural recognition methods that employ ARG theory to recognize built-up objects. We use attributed relational graphs to describe image scenes and models and FSD is introduced to determine the distance between a scene and a model. For each model in NSMB, particular algorithm is designed; therefore the matching can easily be processed in parallel. Together with the matching model, NL attributes of regions provide information for region overlapping, thus separated objects can be extracted from origin images. The NSMB, which contains 38 different models now, is the most significant component in this system and directly decides the performances. Obviously our model base is incomplete and the sample images are comparatively simple, so improvement on performance should be strived for in further practice by the NSMB perfection.

ACKNOWLEDGMENT

This work was supported by Nanchang Railway Administration and Wuhan Zhiheng Tech. Ltd. Co.

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