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SAND2014-1405
Unlimited Release
Printed February 2014

Encoding and Analyzing Aerial Imagery Using Geospatial Semantic Graphs

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Abstract

While collection capabilities have yielded an ever-increasing volume of aerial imagery, analytic techniques for identifying patterns in and extracting relevant information from this data have seriously lagged. The vast majority of imagery is never examined, due to a combination of the limited bandwidth of human analysts and limitations of existing analysis tools. In this report, we describe an alternative, novel approach to both encoding and analyzing aerial imagery, using the concept of a geospatial semantic graph. The advantages of our approach are two-fold. First, intuitive templates can be easily specified in terms of the domain language in which an analyst converses. These templates can be used to automatically and efficiently search large graph databases, for specific patterns of interest. Second, unsupervised machine learning techniques can be applied to automatically identify patterns in the graph databases, exposing recurring motifs in imagery. We illustrate our approach using real-world data for Anne Arundel County, Maryland, and compare the performance of our approach to that of an expert human analyst.

Acknowledgments

We would like to acknowledge Dr. David LaGraffe and Dr. Alex Slepoy, with the DOE/NNSA Office of Nonproliferation Research and Development (NA-22), for their support of this project. Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energys National Nuclear Security Administration under contract DE-AC04-94AL85000.

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Introduction

Collection platforms ranging from UAVs to satellites are able to obtain a vast quantity, on a daily basis, of aerial imagery. Unfortunately, progress in analytic capabilities for investigating this data have lagged those of the collection systems, such that analysts are unable to process the vast majority of collected data, and automated methods are unable to currently identify patterns of interest with sufficient accuracy [3]. This is a well-known problem within the intelligence community, and persists beyond the vast investment (quantified in terms of billions of dollars) in algorithms for feature detection, conducted over the past 40 years.

We argue that one key cause of the current state of analytic tools for imagery analysis lies in the overwhelming focus of those tools on pixel-based analysis, e.g., as embodied in commercial analysis tools such as ENVI (`http://www.exelisvis.com/`). While critical for identifying low-level features, including buildings, trees, roads, and vehicles, they do not inherently provide a linkage with the higher-level relationships and context in which analysts conduct their functions. In this report, we introduce a specific technology – the geospatial semantic graph – for capturing the content of images in terms of high-level concepts and relationships. Key advantages of this encoding scheme include:

1. **Compression:** Due to their level of abstraction, geospatial semantic graphs can facilitate significant reduction in the volume of data that must be stored.
2. **Template-Based Search:** The geospatial semantic graph formalism enables specification of intuitive search templates, which can be used to efficiently query large geographic regions for patterns of interest.
3. **Unsupervised Pattern Extraction:** Unsupervised machine learning techniques can be leveraged to automatically identify recurring motifs in imagery.

The purpose of this report is to document, at a high level, the key concepts and algorithms underlying our approach to analyzing imagery with geospatial semantic graphs. Specifics of particular components of the significant computational pipeline that underpins the research are deferred, in order to allow for focus on communication of the concepts and potential utility of the architecture.

The remainder of this report is organized as follows. We detail our approach to encoding imagery via semantic graphs in Section . The outcome of this process is a database of imagery, which can be exploited in two manners. The first, the use of search templates, is described in Section . The second, the use of unsupervised machine learning techniques, is preliminary, with description deferred to Section . Building on these technologies, we perform a case study on real-world imagery from Anne Arundel County, Maryland, in Section . Our results are contrasted with those obtained by a human expert analyst in Section . We conclude with a summary of our results in Section .

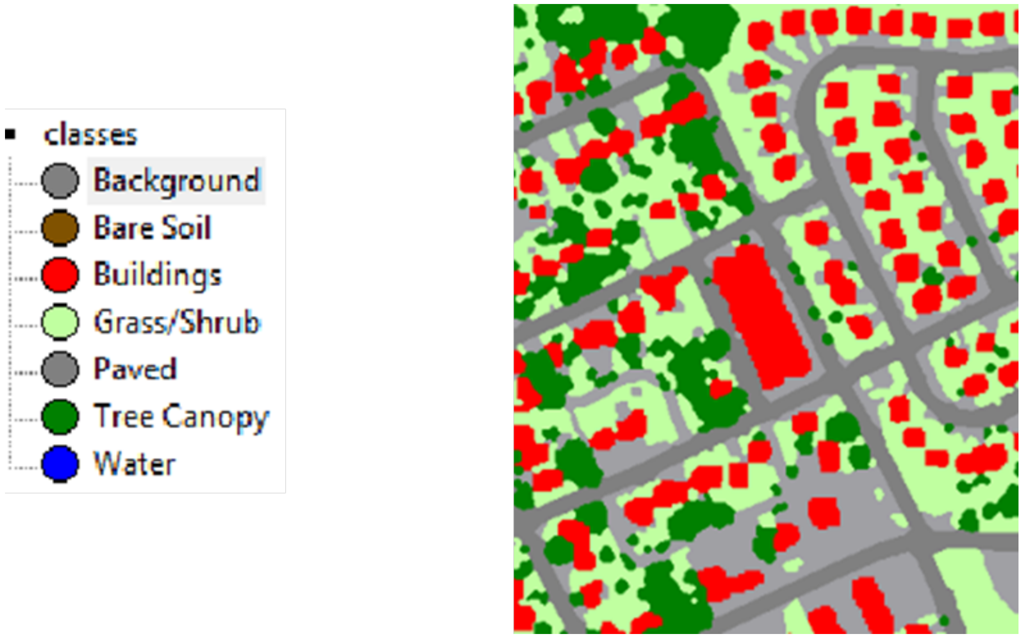

Figure 1. An illustrative example of land use categories in imagery from Jefferson County, West Virginia, extracted via a rule set executed by eCognition software.

Encoding Imagery via Semantic Graphs

The intent of geospatial semantic graph technology is to build upon the significant existing body of research on algorithms for pixel analysis and identification of low-level objects in images. Specifically, we assume that input data has been classified – *on a per-pixel basis* – into one of any number of "land use" categories, e.g., bare soil, paved road, or building. Note that land use categories are very simplistic; we are interested in classifications to identify the concept of a "building", as opposed to the more detailed description of, e.g., an "aircraft hanger". This approach leverages and critically relies upon the significant existing research in pixel analysis and feature recognition, embodied in widely used commercial tools such as ENVI and eCognition (`http://www.ecognition.com/`).

An illustrative example of land use classification of imagery is provided in Figure 1. In the left portion of the figure, we show the color codings for each of a number of land use classifications. In the right portion of the figure, we show a small chip associated with a suburban area in Jefferson County, West Virginia, whose pixels are classified according to the land use categories indicated previously. This particular analysis, and the case study analysis described subsequently in Section , were performed using the eCognition software package executing a detailed classification rule set developed by one of our collaborators, Jarlath O'Neil Dunne. Mr. O'Neil Dunne is the Dirctor of the UVM Spatial Analysis Laboratory at the University of Vermont.

Given an image with pixels encoded according to land use categories, the first step in our

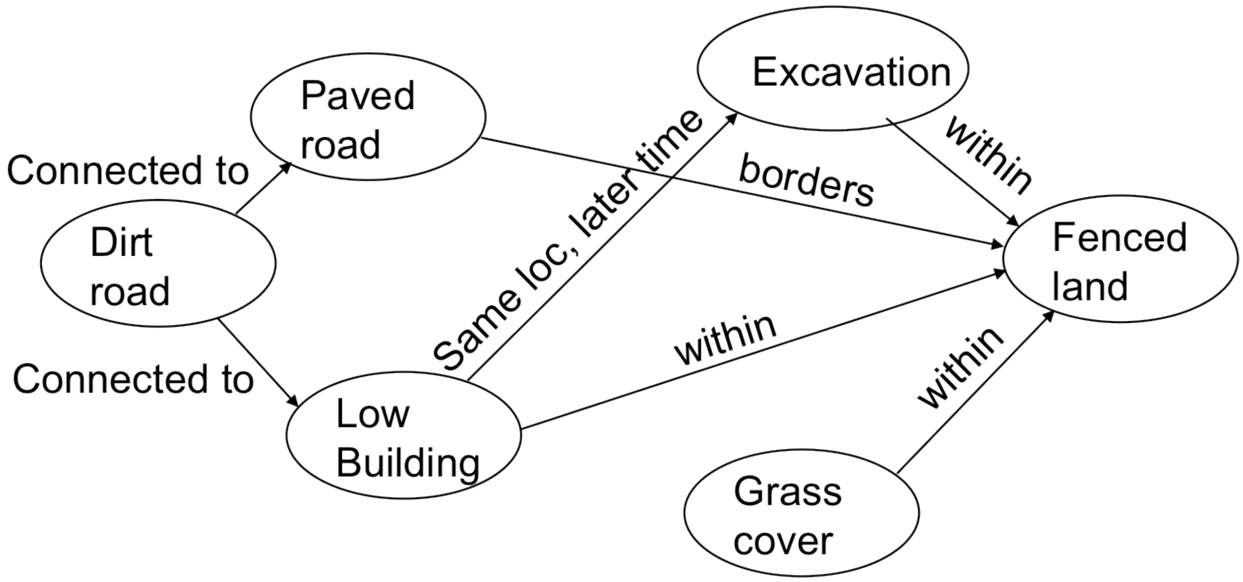

Figure 2. An example of a geospatial semantic graph. Nodes in the graph represent atomic features in imagery, while edges represent geospatial relationships between these atomic features.

computational pipeline is to transfer the pixel-based representation into a set of disjoint (non-overlapping) polygons. Each polygon corresponds to a contiguous region of pixels representing the same land use category. The purpose of this initial transformation is to identify atomic features in the imagery, and their extent. For example, a group of pixels classified as "building" is mapped into a single polygon labeled as "building", with geographic extent and associated descriptions. There is no restriction on the nature of the resulting polygons, in that they may – and are likely to be – non-convex, irregular, and possess "holes". The details of this translation process are significant, and are not described here for purposes of brevity. In summary, the extracted polygons represent low-level, atomic features present in an image.

The objective of our proposed approach is to capture *both* low-level features in imagery and key relationships between them, to facilitate higher-order reasoning and analysis. To accomplish this goal, we leverage the notion of a *geospatial semantic graph* – borrowing key concepts from the field of Artificial Intelligence, where fundamental ideas underlying a semantic graph were first developed. A semantic graph (also called an attributed relational graph [1]) is a graph structure in which vertices (i.e., nodes) represent concepts, and edges represent relationships between concepts. A geospatial semantic graph is simply a semantic graph in which the concepts and associated relationships are associated specifically with geospatial data. An example of a geospatial semantic graph is provided in Figure 2. The purpose of a geospatial semantic graph associated with an image is to capture the key features and their geospatial relationships in a concise manner.

Each polygon extracted from land-use-classified pixels corresponds to a node in a geospatial semantic graph. To compute the edges in a geospatial semantic graph, we leverage the CGAL (Computational Geometry Algorithms Library – `https://www.cgal.org/`). The CGAL is a widely used, freely available library originally intended to support storage and query of polygons associated with VLSI / microprocessor designs. We leverage the library to compute relationships between the polygons, which in turn define the edges in a geospatial semantic graph. For example, geospatial operations such as “contains” (e.g., a fence surrounding a building) and “nearest-to” (e.g., the nearest road to a building) correspond to operations over a set of polygons. The CGAL facilitates efficient computation of such operations, providing – in conjunction with the polygon extraction procedure introduced above – the final component necessary to translate pixel-based, land-use-classified representations of images into their geospatial semantic graph analog.

It is important to note that in contrast to standard graphs and many semantic graph representations, the nodes and edges in geospatial semantic graphs are *attributed*. In other words, they are tagged with auxiliary information concerning the atomic features and their relationships. For example, nodes representing buildings may be tagged with their square footage, and edges representing “nearest-to” relationships may be tagged with the distance between (the centroid of) the objects.

We have been intentionally vague concerning the specific types of nodes and edges represented in a given geospatial semantic graph. The specific types of nodes and edges ultimately depend on the nature of the analysis that is of concern. For example, military analysts proceed using a different language and different concepts (together, loosely an “ontology” or domain of discourse) than municipal analysts. Ultimately, it is likely that the computational pipeline described in this section will need to be specialized to the specific analyst community that it is intended to support. We discuss a specific categorization below when discussing our case study, in Section .

Finally, we briefly comment on the issue of linking the geospatial semantic graphs associated with distinct adjacent or overlapping images. In general, we assume that imagery is overlapping, such that shared common features can be identified between adjacent images. This allows for compaction of multiple geospatial semantic graphs into a single large geospatial semantic graph, if desired, and avoids issues relating to search templates crossing multiple images.

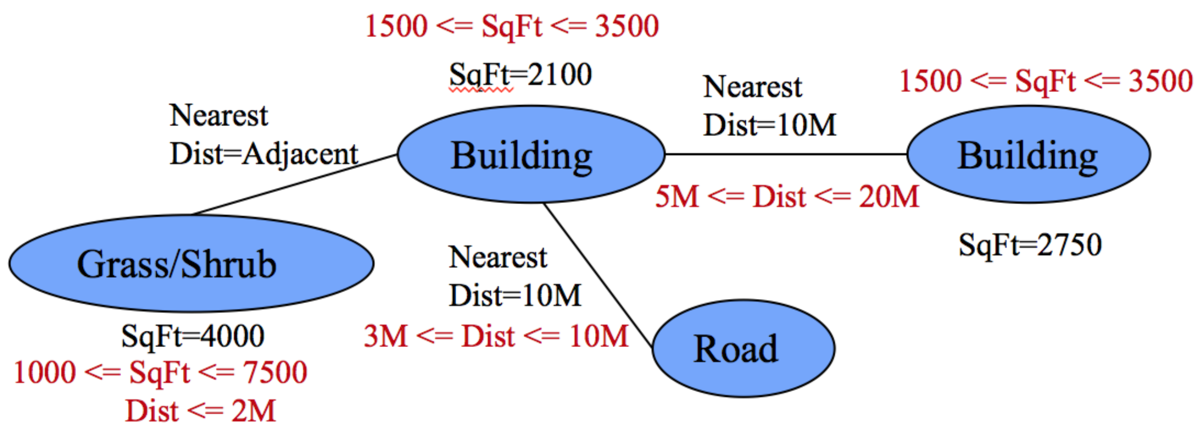

Figure 3. A sub-graph template specifying characteristics that define a typical suburban tract house.

Pattern-Matching in Semantic Graphs

Given a geospatial semantic graph encoding of a set of images, the next obvious question is: How can we efficiently search this graph for patterns of interest? By "patterns of interest", we are referring to patterns ranging from facilities with very specific and differentiating characteristics (of which only a few may be exist) to broad, common motifs routinely found in imagery, e.g., a suburban house. A straightforward method to specify patterns of interest – at a high level of abstraction – is via the use of *sub-graph templates*: small geospatial semantic graphs coupled with constraints on node and edge attributes.

In Figure 3, we show an example of a sub-graph template specifying key defining characteristics of a suburban tract house. The nodes and edges represent key characteristics that must be present in any match, coupled with constraints on attributes, which serve to further refine the match criteria. As the example illustrates, such sub-graphs are generally simple to specify and intuitive in nature. We defer the question of whether such templates can be used to identify features in large-scale scale data to our case study in Section .

Given a sub-graph template, the next question is how to identify corresponding matches in a geospatial semantic graph. The answer to this question comes in the form of algorithms for solving the *sub-graph isomorphism*[2], which is a formal description of the problem of locating all instances of a sub-graph that is embedded in a larger graph.

Algorithms for solving the sub-graph isomorphism problem fall into two categories: exact and inexact. Exact methods yield optimal matches, but are generally computationally intractable; formally, sub-graph isomorphism is NP-hard. Inexact methods may miss matches, but are more computationally efficient. In our computational pipeline, we use the approximate matching algorithms for sub-graph isomorphism implemented in Sandia's MTGL (Multi-Threaded Graph Library) software package `https://software.sandia.gov/trac/mtgl`[5]. Note that the MTGL algorithms are used to find candidate matches, which are subsequently filtered, as they are not capable of dealing with constraints on node and edge attributes.

While sub-graph isomorphism is theoretically difficult, the computational challenges in geospatial semantic graph contexts are not significant. First, the presence of edge and node attributes can yield large reductions in the cost of search. Second, because geospatial relationships between objects do not span significant distances (e.g., there is unlikely to be an edge between buildings separated by miles), geospatial semantic graphs are approximately planar; the imposition of such constrained relationships between nodes can yield significant reductions in search cost. In particular, this property allows geospatial semantic graphs to be tiled or partitioned in an overlapping manner (to deal with truncation effects), such that the individual partitions can be searched independently and in parallel.

In the framework described above, we assume that analysts are interested in obtaining *exact* matches to templates. In practice, this is not the case, principally because analysts are often unsure of precise template characteristics, such that inexact matches are useful when initially developing templates. Extension of our framework to include inexact matches is beyond the scope of this report, but is an avenue of research under active investigation.

Ultimately, we envision two primary use cases for template matching in the context of geospatial semantic graph analysis. The first involves identification of well-known motifs in imagery, e.g., houses and neighborhoods. As indicated in our case study below, a very large proportion of primitive objects can be categorized into one of a handful of sub-graph templates. Objects that are not captured in common templates are, almost by definition, of interest to analysts. The second involves the ability to quickly answer "what-if" questions, in which analysts use sub-graph templates to quickly determine whether a hypothesized pattern exists in a particular set of images.

Case Study

We now demonstrate our approach to analyzing imagery via geospatial semantic graphs, using a conceptually easy task: that of automatically locating high schools in the US. As we will show, high schools are conceptually simple to describe in a geospatial semantic graph context, but not a pixel-based context. We use 6-inch resolution multispectral and LIDAR data for Anne Arundel County, Maryland. This data was generated by an aerial survey, and is part of a larger set containing all counties in the Baltimore-DC corridor. Anne Arundel County is approximately 50 miles by 60 miles, yielding roughly ten billion pixels at the given resolution. The data was processed and tagged with land use classifications using a rule set for the eCognition software package, developed by our collaborator at the University of Vermont.

We begin by asking the natural question: What features make a facility a high school? In other words, what is a high school in terms of atomic geospatial features and relationships between those features. A first attempt at such a description would yield, at least in much of the US, three core features: a football field, campus buildings, and a parking lot. Expanding on each of these features, we observe the following:

1. **Football Field**: Is of type “Grass/Shrub”, with a bounded area and specific dimensions.

2. **Campus Buildings**: Is of type “Building”, has a specific range of square footage, is within 100 meters of a parking lot, and is within 300 meters of a football field.

3. **Parking Lots**: Is of type “Other/Paved”, with a bounded area.

While simplistic, this set of attributes captures – at a conceptual level – the key characteristics of a US high school, at least in the greater DC metropolitan area. Generation of this textual description does not require expert imagery analysts, and can be (and was) accomplished quickly in an informal group discussion session.

Given such a description of a specific facility or type of facility of interest, the next step in the process of geospatial semantic graph-based imagery analysis is to convert the description into a sub-graph template. In this case, the translation process is straightforward, with the result shown in Figure 4. The sub-graph template captures, in a graphical manner, the primitive objects in the template, their attributes, and their inter-relationships.

There are twelve public high schools in Anne Arundel County. Each of these high schools is shown in Figure 5. They are displayed independently in roughly a 2000 meter by 2000 meter “chip”, with pixels colored by their land use classification. The primary feature to note among the high schools is that they are topologically quite distinct: the number and mix of parking lots and buildings is disparate, there is a large range of building and parking lot sizes, there is no commonality in terms of surrounding features, and the orientation of the key features (the buildings, parking lots, and football field) is heterogeneous. Automatic identification of high schools in this context is therefore remarkably challenging, despite the conceptual simplicity of the problem.

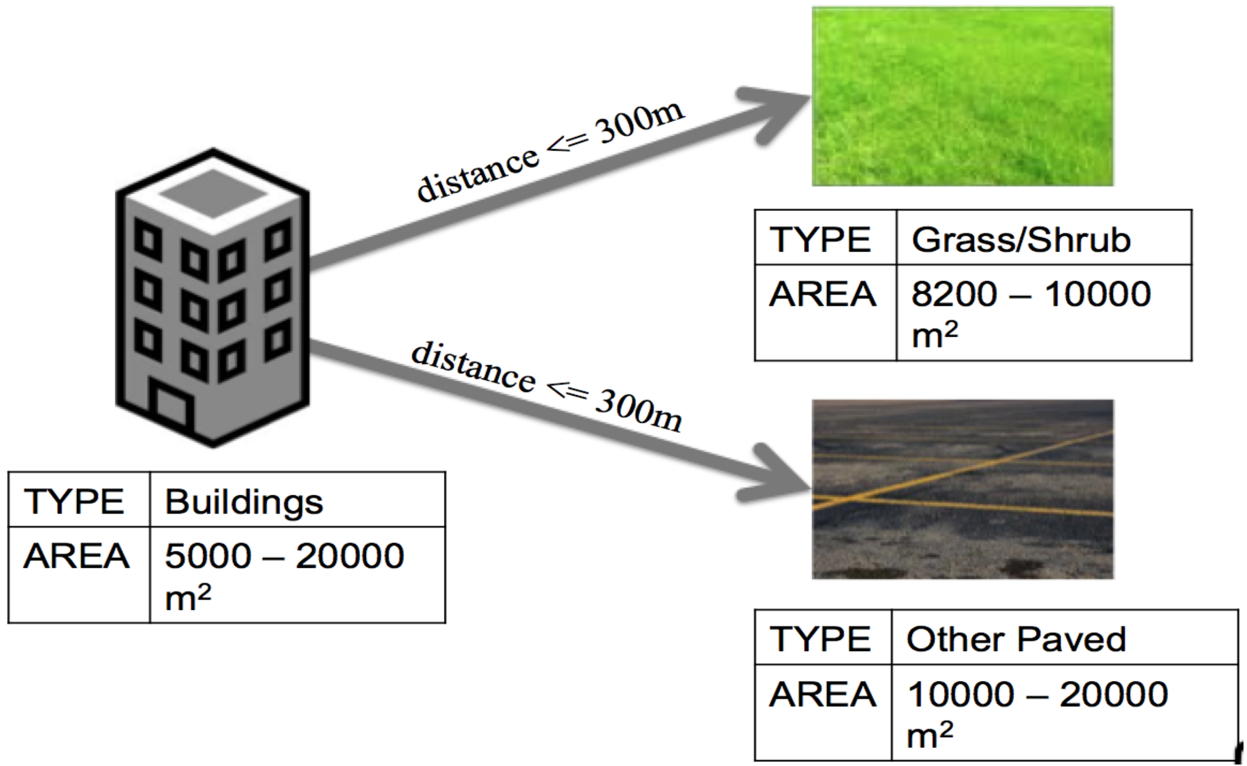

Figure 4. Our initial sub-graph template specifying high schools in the United States.

Our high school sub-graph template was developed prior to viewing any of the data associated with Anne Arundel County. Then, given the real data, we performed two iterations of modifications on the template, which were restricted to minor changes to the range of attributes specified by feature constraints (e.g., parking lot area). Following this initial tuning process, we executed sub-graph isomorphism – using our refined high school sub-graph template – on each of the image chips shown in Figure 5. The purpose of this test is to verify that we can find the matches when focus is restricted; if this is not possible, then there is no hope when we expand the analysis to effectively unrestricted search domains. The net result yielded successful identification of 11 of the 12 high schools, with no false positives (which are admittedly unlikely given the size of the test images). The failed case was in retrospect due to incorrectly classified pixels at the interface of the high school's football field and surrounding track. This failure is an instance of the "garbage in, garbage out" analysis principle, and highlights the need for accurate upstream analysis in order to correctly identify primitive object features.

Overall, the results are extremely encouraging and indicate that a simple sub-graph template can be used to both represent and identify topologically diverse facilities, with high accuracy. An example of a topologically simple high school is shown in Figure 6. Here, we see a single building, a compact parking lot, and the requisite football field. In this case, the alignment with the sub-graph template is straightforward. In contrast, a significantly more topologically complex example is shown in Figure 7. In this case, the high school is co-located with a middle school (a

Figure 5. The twelve public high schools in Anne Arundel County, Maryland.

not uncommon occurence), such that there are numerous buildings and parking lots in the same vicinity. Yet, despite the presence of such “noise”, the matching process accurately identifies the high school. Further, this example actually shows two possible matches – both the middle and high school are independently identified as possible matches with the football field.

In our next test, we broke up all of Anne Arundel into large tiles that covered all of the county, as shown in Figure 8. This was necessary as the data structures could not hold (due to implementation details) the entire county data set. We then executed sub-graph matching on each of the tiles, using the high school template. As expected, we again found all (following correction of the land use classification data associated with the one high school that we initially failed to identify) of the 12 public high schools. However, we additionally found two false positives. The first is shown in Figure 9. Upon investigation, one might naturally ask: Why *isn't* this a high school? Further analysis confirmed the facility is actually a high school – just not a public high school. Rather, it is a private high school, which was not found in our initial search of Anne Arundel registrations.

The second false positive is shown in Figure 10. In this case, cursory analysis confirms that the facility is likely not a high school, but rather a facility in an industrial park. While not shown in the graphic, the upper portion of the excavation zone was a grass field in the original source data on which the land use classification process was executed (the image shown is from Google Earth). Fortuitously, the dimensions of this field correspond to those of a football field. Coupled

Figure 6. Topologically simple example of a positively identified high school in Anne Arundel County.

with building and parking lot areas consistent with the template, a positive match was therefore reported. This result demonstrates that our approach, while maintaing high overall accuracy, is not infallable. Rather, our false positive rate is sufficiently low as to not overwhelm analysts with irrelevant matches.

Overall, this case study serves as an illustrative example of the *potential* power of the sub-graph template approach to automatic analysis of geospatial semantic graphs associated with imagery. We have also used the approach to identify golf courses and houses associated with higher-income neighborhoods in Anne Arundel. However, we have not explored the full power nor the limitations of our approach. In particular, a key question that remains to be answered is the limit on the complexity of specific facilities that can be identified, specifically due to limited numbers of land use categories.

Figure 7. Topologically complex example of a positively identified high school in Anne Arundel County.

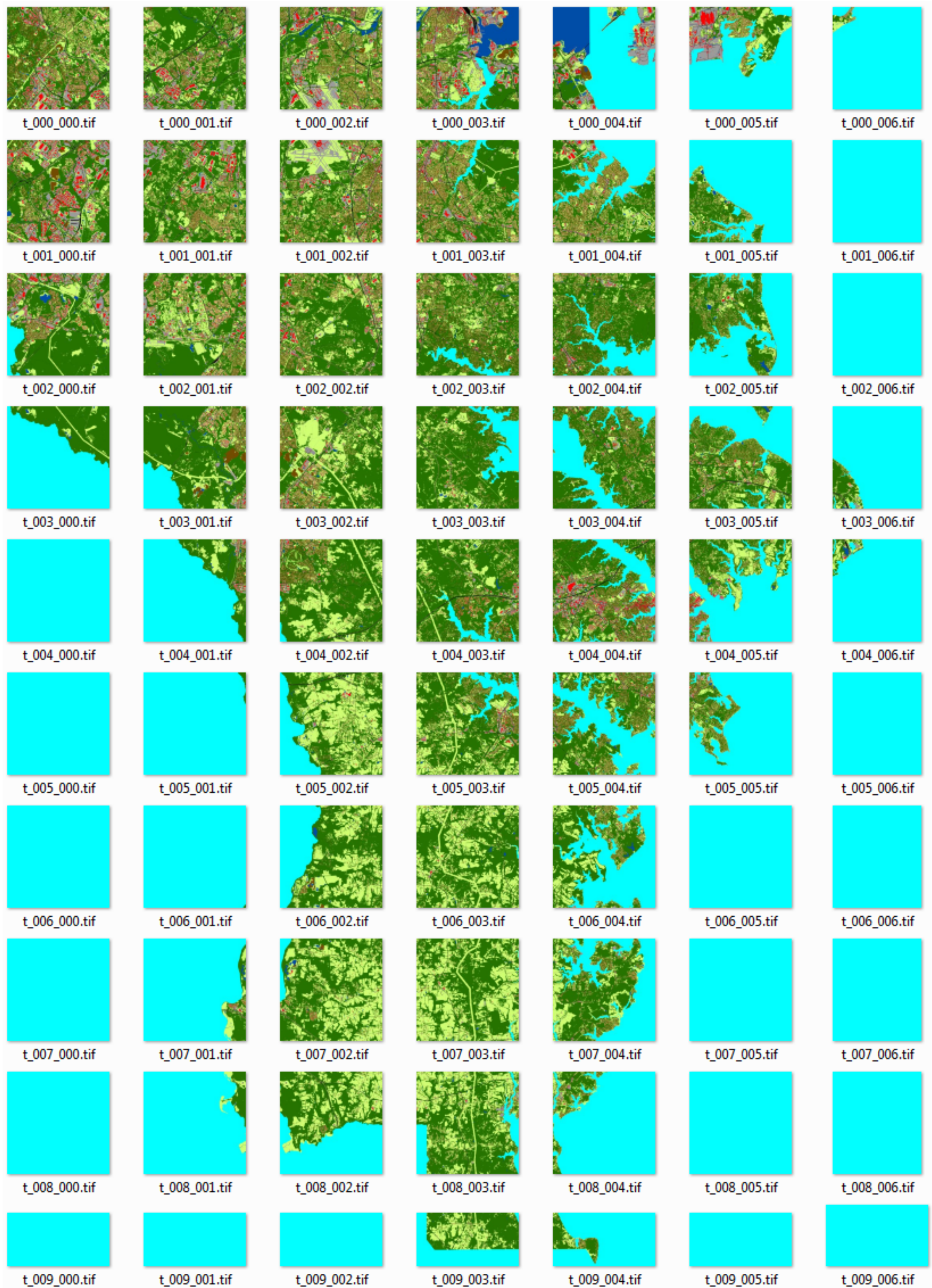

Figure 8. The set of tiles used to run the sub-graph matching on the entire Anne Arundel County data set.

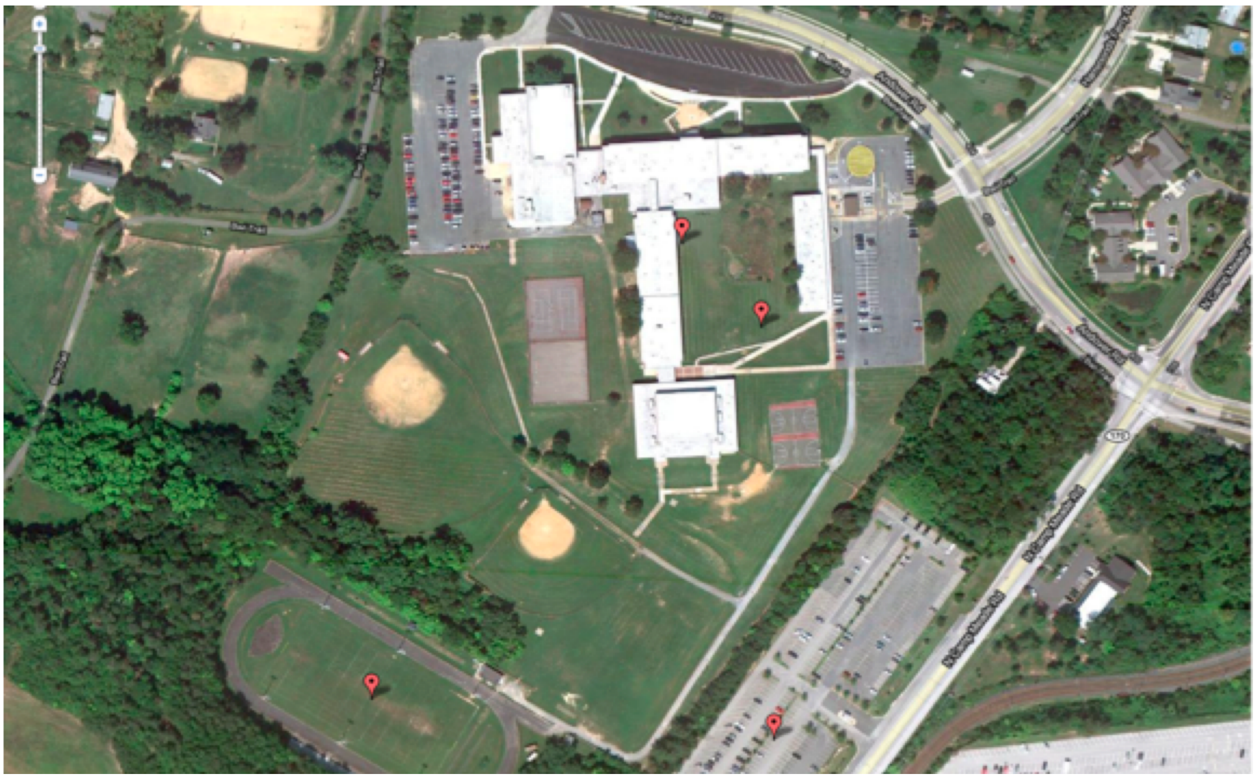

Figure 9. A “false” positive identified by sub-graph template matching; the object is a private high school in Anne Arundel County.

Figure 10. A confirmed false positive identified by sub-graph template matching in Anne Arundel County.

Performance Relative to a Pixed-Based Approach

To compare the performance of our approach relative to the best available pixel-based analysis methods, we again engaged our expert collaborator at the University of Vermont, Jarlath O'Neil-Dunne. Besides supplying us with the initial land use classification data, he is an expert in the use of traditional geospatial imaging software and is well known in the community for his web tutorials using eCognition software.

Mr. O'Neil-Dunne attempted the same larger goal as we described in Section : finding all of the public high schools in Anne Arundel County, Maryland. In his experiments, Mr. O'Neil-Dunne used land use classification data and all of the tools that were available to him in the eCognition software suite. After two weeks of intensive effort, he achieved manage a 75% identification with significantly more false positives than we obtained. Additionally, running and refining the search was considerably more difficult than it was when using the geospatial semantic graph approach. It is also important to point out that this simple search template pushed the eCognition software to its limits as far as the complexity of describing the problem; a more sophisticated template would probably not have been possible to analyze using the tools available in eCognition and other state-of-the-art image analysis tools.

Figure 11. Result of k-means clustering on a vector encoding of a geospatial semantic graph corresponding to a portion of Jefferson County, West Virginia.

Unsupervised Learning for Pattern Identification

Although less developed than our sub-graph template approach to imagery analysis, unsupervised learning techniques can also be leveraged to automatically identify recurring patterns in geospatial semantic graphs. In particular, machine learning algorithms such as clustering can be used to identify recurring motifs in large geospatial semantic graph databases. While we have not developed this avenue of research to the extent that we have for sub-graph template matching, we have executed a proof-of-concept demonstration, which we will now describe.

We consider an example in which we are given a particular geospatial semantic graph. The first challenge is to transform this graph into an input representation appropriate for a typical machine learning algorithm. Generally, machine learning algorithms operate on real-valued vectors of input data. To convert a geospatial semantic graph into a set of vectors, we focus on the vertices in the graph. For each vertex, we create a vector describing its type and attributes (e.g., building area), in addition to attributes of key edge relationships (e.g., distance to the nearest road, distance to the nearest non-adjacent grass area). Given this set of vectors, we can then leverage a machine learning algorithm to identify patterns in the geospatial semantic graph.

An illustrative result is shown in Figure 11. This graphic shows the results of k-means clustering [4] applied to a vector encoding of a portion of Jefferson County, West Virginia. We directed the k-means algorithm to partition the data into two clusters; the corresponding categories are denoted by blue and green pins in the graphic, respectively. The results indicate that the k-means algorithm is able to accurately differentiate between the residential buildings in the image and those associated with the race track facility.

While very preliminary, the result is suggestive of the power of automated machine learning algorithms to identify patterns in images encoded as geospatial semantic graphs, using both k-means and more advanced clustering and classification algorithms.

Conclusions and Future Research Directions

The purpose of this report is to both document a novel approach to encoding and searching imagery via geospatial semantic graphs, and to demonstrate the potential of the approach on a case study, using real-world data. Our case study – finding high schools in the US – strongly demonstrates the potential power of our approach. In particular, we could find all of the target facilities using an easy-to-describe sub-graph template, and found only one significant false positive. In contrast, the performance obtained by an expert human analyst using pixel-oriented anlaysis is significantly worse, with more misses and false positives, and requires significantly more time to conduct.

While we have demonstrated the potential power of our novel approach to analyzing geospatial semantic graphs, a number of significant research challenges must be addressed before the paradigm can be implemented in real-world analysis environments. These include representation and specification of temporal changes in imagery (to support change detection and patterns-of-life analysis), partial sub-graph template matching (to provide for less rigorous match criteria), and semi-supervised learning of sub-graph templates (contracting the time required by analysts to create search templates).

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