MODELING AND DETECTING CHANGE IN AN INTEGRATED SPATIOTEMPORAL ENVIRONMENT

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ABSTRACT

Current geographic information systems tend to follow an inherently static approach to geospatial information management. Small amounts of information are typically synthesized into map-like application-specific data snapshots. This static approach leaves large amounts of information unused and offers limited communication capabilities. Accordingly, it is unsuitable for today's applications, where geospatial information becomes increasingly dynamic and spatiotemporal in nature. In this paper we present a framework for the integration of digital images and complementary GIS datasets in a model which provides explicit information about spatiotemporal change. We propose the *SpatioTemporal* Gazetteer as a model that makes more effective use of multiple information resources than the traditional map model, and in particular incorporates components to track changes to objects over time. We present the general components of the model and discuss information flow in such a system. We also present a digital image analysis method, based on least squares template matching, to identify object outline change in sequences of digital images. This is a fundamental process within our integrated environment, as it integrates object extraction from digital imagery with change detection. The theoretical model for this method is presented together with experimental results.

1 INTRODUCTION

In current geographic information systems only a small fraction of potential information resources is handled. A relatively small amount of information is synthesized into map form while a large body of information remains unused. It is common practice to have multiple sources of information containing multiple representations of features are reduced to a single representation. This process can eliminate useful information and particularly information on change. Change, whether it is the very dynamic change of mobile objects, periodic fluctuations of fixed objects, abrupt change such as that resulting from catastrophic events, or more routine incremental change, is valuable information which an information system should provide direct access to. Information on change is important to better understand why certain conditions exist –either now or in the past– and to make predictions of what the conditions or configurations of an entity will be at some future time. We propose the *SpatioTemporal* Gazetteer as a model that makes more effective use of multiple information resources than the map model, incorporating in particular components to track object changes over time. The Gazetteer is part of a broader framework for the representation of geographic change and more direct access to change information. Our spatiotemporal model is roughly based on a digital library model (Beard and Smith 1998, Beard et al 1997, Goodchild 1998). The model consists of a repository of heterogeneous information sources, with a set of indexing structures to organize and access them (see Figure 1). The approach shares some of the characteristics of the multimedia geographic information system proposed by (Lombardo and Kemp 1997) and symbolic description of image sequences using spatiotemporal logic (Del Bimbo et al 1995).

In this paper we will provide an overview of our model and its major components and operations. Furthermore, as digital images are the major source to capture information in today's geospatial applications, we present a novel digital image analysis method, based on least squares template matching, to identify object outline change in sequences of digital images. This is a fundamental process within our integrated environment, as it integrates object extraction from digital imagery with change detection in a single process. We present the theoretical model for this method, and experimental results.

In Sections 2 and 3 we present the essential components of our *SpatioTemporal* Gazetteer and discuss their interaction. Our image-based change detection technique is introduced in Section 4 together with experimental results. Our final Section (5) provides the essential conclusions of our approach.

2 THE MULTIMEDIA INFORMATION STORE

The repository of information sources is referred to as the *multimedia information store* (MIS). It can include imagery, maps, video, various types of scientific data sets (e.g. meteorological or oceanographic observations), and even digital files of text documents (e.g. books, newspaper reports, and magazines). The multimedia information store is intended to act as a continually growing repository, with new information potentially added on a daily or even more frequent basis. This repository need not be a single site, but could be a multi-node distributed repository. The nodes of the National Spatial Database Infrastructure are an extreme example of such a virtual repository.

Individual units within the information store are *information objects*. They can be for example maps in a digital format or digital images. Ingest of information into the store requires, at a minimum, creation of metadata elements that include:

- a unique identifier for each information object (an object ID number),
- an assignment of information type (e.g. image, map, video),
- a spatial footprint (e.g. the geo-coordinates of the corresponding geographical area), and
- a time stamp (the date in which the object was generated, or the date to which the object refers).

Additional information may include source-specific information (e.g. calibration data, orientation parameters, and accuracy estimates for an aerial image) and other semantic information (e.g. dataset provider).

The object identifier may be organized as a database structure ID, in a way that contains some of the remaining information. In this sense, instead of simple sequential ordering, the identifier becomes a composite of alphanumeric fields. For example, the first set of alphanumeric characters may express the type of information.

This multimedia store is an *implicit* information store. The term implicit is used to emphasize the fact that individual information objects within MIS contain a large volume of latent information. Furthermore, there exist even greater volumes of implicit information in combinations of information objects like maps and images. Higher levels of spatiotemporal reasoning are achieved through the synergetic use of multiple datasets (e.g. the differential analysis of image sequences, or the combined analysis of images and maps).

3 THE SPATIOTEMPORAL GAZETTEER

The *SpatioTemporal Gazetteer* is an indexing structure over the multimedia information store. It is also the key mechanism for converting the latent information contained in the multimedia information store into explicit change information. Gazetteer components convey information on primitives of change. These primitives can be converted to explicit complex change information by operations over the gazetteer sub-components.

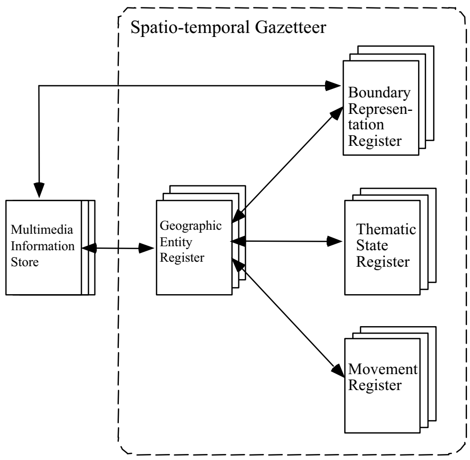

Figure 1. Conceptual model of integrated spatio-temporal gazetteer and multimedia information store.

The gazetteer stores representations of identifiable, *spatiotemporal entities*. For brevity we will be using the term *S-T entities* in this paper. They can be:

- *physical* objects (such as roads, buildings, islands, or mountains), or
- *conceptual* objects (such as nations, states, and counties), or even
- *spatiotemporal incidents* (such as floods, earthquakes, or even territory annexations).

All these types of information are characterized by some type of space-time coordinates. Either one or both of these coordinates may be precise or, to a certain degree, fuzzy. For example, the duration of a flood may be difficult to pinpoint, and the same may be said about its spatial extent. The gazetteer comprises sub-components that describe specific entity properties. The objective is to have minimal overlap between components, while maximizing their aggregate content. One such partitioning is offered by the four components of Fig. 1, namely a geographic entity register, a boundary representation register, a thematic state register, and a movement register.

☞ Geographic Entity Register

The *geographic entity register* maintains a record of identified spatiotemporal objects. When an object is identified and registered it receives:

- a unique *identifier* (geographic entity identification number),

- a description of the object class (e.g. building),
- an initialization of its lifespan index, and
- a generalized, approximate spatial location or footprint (e.g. the geo-coordinates of the corresponding geographical area, or even the identifying ID of a broader geographic region).

The above information is in analogy to the registration information used in the multimedia information store, but refers to a specific object instead of a dataset.

☞ Boundary Representation Register

The *boundary representation register* is a collection of spatial descriptions for specific objects. Each spatial representation of a geographic object is contributed by a specific information source. For example a map in the information store may contain a detailed 2D representation of a lake, a satellite image may have a coarse 2D representation of the same lake, and a stereomodel may contain a detailed 3D representation of the lake. A relation in the spatial representation register contains:

- a geographic object ID,
- an information object ID (linking to the source of the information),
- the time stamp of this information object (transferred to the specific geographic object),
- the spatial representation of the geographic object as extracted from the information object (e.g. vectorized or raster outlines, with or without accompanying radiometric information), and
- information for the extraction method (especially focusing on the relevant accuracy estimates).

Alternatively, we can replace multiple boundary representations by the storing of an initial state and subsequent changes. In this case, an object representation at time t^n is obtained as the aggregation of t^0 and all subsequent changes ? $t^{i-1,i}$, for i=1,… n. Some information sources (sensors) are designed to record a change of state the moment it occurs (e.g. a flood gauge) in which case the time stamp is the instant of change. Other information sources can document changes of state but not exactly when they occurred. This is typically the case with satellite imagery. As an example an image can record that a house burned down but not necessarily when. An attribute of an information source will be whether it is capable of recording the exact time of a state change.

☞ Thematic State Register

The *thematic state register* is another collection of attributes for geographic objects. It tracks states of geographic entities as provided by specific information objects. States are multidimensional so a geographic object may have several concurrent states. A house for example may have the concurrent states: exists, has new owner, has new roof, is in violation of a zoning ordinance. Accordingly, the thematic register includes relations between geographic objects and source information objects. An individual information object can contribute information on one or more states. Information in the thematic state register consists of a geographic entity ID, the ID of the information object from which states were extracted, the time stamp of the information object, and states of the object at that time point. Similarly to the geographic register, the thematic may be a differential register, by recording changes in, instead of multiple versions of, objects.

☞ Movement Register

The *movement register* is a collection of relations between geographic entities and pairs of information objects. For entities other than those strongly fixed in a location, it tracks their movement. This is a differential register, since movement of an object can not be detected from a single information source (a single frame in the case of video). Detection of movement requires at least two information sources with different time stamps defining a time interval. A record in the movement register contains the unique ID of a geographic object, shift and/or rotation information indicating movement of the geographic entity, the IDs of the two information objects from which motion information was extracted, and the time interval computed as the difference between the two information object time stamps.

4 IMAGE-BASED CHANGE DETECTION

4.1 Description of the approach

The identification of changes in object outlines is a fundamental operation within our model. The method we are presenting here employs least squares matching for the detection and tracking of edges in digital images (Gruen 1985, Gruen and Agouris 1994, Gruen and Stallman 1993). A window depicting an edge pattern is introduced as a reference template that is subsequently matched to digital image patches in the vicinity of actual edge segments. Old object vector information is retrieved from our spatiotemporal Gazetteer (Fig. 2). Using positional information for the vector and georeferencing information for a new image, we transfer the old object information onto the new image. There, it is

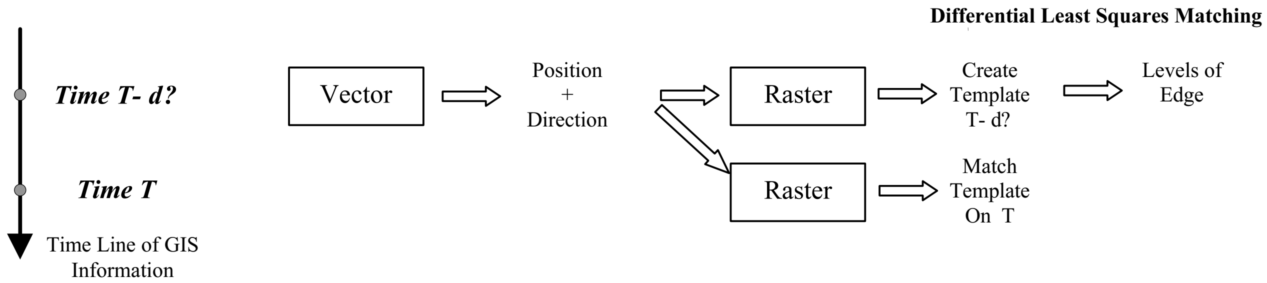

Figure 2. Process flowchart for outline change detection to update spatial register information.

used as input for a differential application of least squares template matching (DLSM). Older information in raster format, also retrieved from the Gazetteer, produces edge templates that are matched to the image. By matching an edge template to the image we identify outline locations in this image as conjugates to template edge locations. Thus we transfer the high accuracy potential of least squares matching onto object extraction. By performing this process at select positions along the object outline, we compare the complete object to its last recorded information. Changes are identified as instances where DLSM fails to match adequately.

4.2 Mathematical Model

We define *f(x,y)* to be the reference edge template created from prior information, *g(x,y)* to be the corresponding image patch in the new information, and *e(x,y)* being the error vector. In our least squares matching method, the two patches are geometrically related through a transformation that may range from a full affine to a simple shift along an axis (if the template is properly resampled to have edges oriented along major axes):

$$X_{New} = X_{Old} + dX \tag{1}$$

In the simple case of shift solution (Agouris et al 2000), the dX parameter is the unknown that allows the repositioning of the image window to a location that displays better radiometric resemblance to the reference template. It is introduced in the derivative terms $(\partial g / \partial x)$ of the linearized observations above as

$$f(x,y) - e(x,y) = g^o(x,y) + g_x d\partial X \tag{2}$$

Regardless of the choice of geometric transformation, the resulting observation equations are grouped in matrix form as

$$-e = Ax - l \quad ; \quad P \tag{3}$$

In this system, l is the observation vector, containing gray value differences of conjugate pixels. The vector of unknowns x comprises the shift at the x direction, while A is the corresponding design matrix containing the derivatives of the observation equations with respect to the parameters, and P is the weight matrix. A least squares solution allows the determination of the unknown parameters as

$$\hat{x} = (A^T P A)^{-1} A^T P l \tag{4}$$

4.3 Object Decomposition

Our algorithm for change detection follows a point matching approach, with prior information applied on a new image. A problem arises during this process related to the points that would sufficiently represent the 3-D object on the 2-D image space. To compensate for that, a 3-D object is expressed through a wireframe representation (de Cambray 1993, Vosselman and Veldhuis 1999), based on prior vector information.

Our algorithm is focused on detecting change in building outlines, so the examined object may be considered as an aggregation of planar surfaces, following the concept of *polyhedral models* (Bignone et al 1996, Hendrickx et al 1997). A generalization of planar surfaces may be performed by assuming that they are equivalently represented by intersections of planes, i.e. by lines. Due to the nature of our raster dataset (aerial photography), vertical aerial photos are assumed to be available, and 3D planes are merged into 2D, by applying an overlay operation on our 3D vector based on our viewpoint perspective.

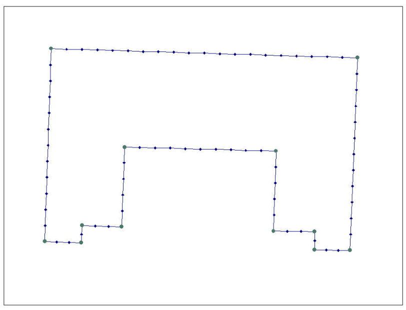

Figure 3. Object Outline Decomposition

To reassure an adequate representation of lines from points , a new element is introduced, the Minimum Spatial Element (MSE) (Mountrakis et al 2000). The MSE describes the resolution of spatial change that the user is interested in. Absolute estimates for this resolution (e.g. 2m, or 0.5 pixel), or relative measures (e.g. the average size of a room) can be assigned. By using this information, we perform a segmentation of outlines, and lines are essentially substituted by the corresponding points along the outline. As corners are defined by line intersections, we do not have to consider them in our outline decomposition. A final product of this process is moving from a 3-D object to a set of points in the 2-D image space (Fig. 3).

4.4 Geometry of the edge

4.4.1 Levels of the edge. In order to take advantage of the raster representation that preexists and enhance the algorithm's performance and liability, a geometric representation of the edge is extracted and included in the DLSM solution. We categorize edges as having two, three or four levels, depending on their type (Fig. 4).

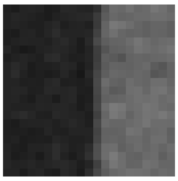

Figure 4a. Two Levels

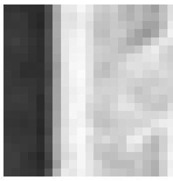

Figure 4b. Three Levels

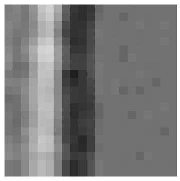

Figure 4c. Four Levels

This corresponds to one, two or three edges on the image. We resample our window so that the edge is perpendicular to the x-axis of the window under examination. Then we calculate the average first derivative of each column, at the X direction:

$$\bar{g}_x(x) = \frac{\sum_{1}^{y} \frac{\partial g(x,y)}{\partial x}}{y} \tag{5}$$

A subset of 80% of the pixels with the lower residuals is used, to compensate for noise. An analysis of the $\bar{g}_x(x)$ graph by using first and second derivatives reveals 3 (or less) maxima. A decision process follows for accepting or rejecting a maximum. First, a check based on maximum value of the maxima is performed, to compare the dominant edge with other gradient maxima to eliminate false responses. For the accepted values, we perform another check by introducing the first derivative along the edge direction. We claim that an edge should have high gray value variations perpendicular to itself, but at the same time low variations along itself. After this filtering, and based on the number of maxima accepted, our edge is considered an edge of type a, b or c (Fig 4).

4.4.2 Expressing edge geometry through the weight matrix. The analysis on prior raster information provided a description of the geometry of the edge that we are trying to match. This geometric information is inserted in our mathematical model by formulating accordingly the weight matrix. We claim that a combination of Gaussian distributions can be applied in order to assign higher weights at the accepted maxima. The formula of the Gaussian distribution is expressed as:

$$G(x) = \frac{1}{\sqrt{2ps}} e^{\frac{(x-m)^2}{-2s^2}} \tag{6}$$

Based on the number of levels three different Gaussians, expressing the weights, can be formed (Fig. 5). Each time the value of the mean ( ) corresponds to the position where the levels change. The standard deviation, like the mean is measured in pixels. After analyzing different scenes of scales varying from 1/4000 to 1 /7000, the following values, depending on the number of levels, were chosen:

- Two levels: $s = 6$ pixels

  The large value of s shows a spread distribution, which is considered valid, since no information for the edge geometry can be extracted.
- Three levels: $s_1 = 1$ pixel, $s_2 = 2.5$ pixels

  The three levels correspond to two edges on the template window. The edge that is closer to the one defined by the vector, is assigned the larger s, since it is the one we are trying to match.
- Four levels: $s_1 = 1$ pixel, $s_2 = 2.5$ pixels, $s_3 = 1$ pixel

  In the case of four levels, the same rule as above is applied. The edge closer to the vector inherits a larger distribution than the other two, and the standard deviations are formed accordingly.

When multiple edges exist, they can result from the actual shape of the edge or random conditions such as noise, shadows, different projections, etc. We compensate for this by introducing a scaling factor describing the *expected* *geometry* of the edge. This is applicable in cases where curbs at the edges of buildings exist. The actual width of the expected curb is translated into pixel coordinates (d), and two Gaussian distributions are created in both sides of the vector edge, based on this distance (Fig 6). The mean is assigned the value of $_{vector} \pm$ d, depending on which side it is. The standard deviation gets the value of 2d/3, so that difference in two pixels results to a 40% reduction of the weight. The values of the Gaussians vary from 0 to a value max. To simplify the process max is assigned to have the value 1. With this, pixels close to the expected distance d will have almost the same weight as the vector edge, while pixels away from that will be scaled down. An example of the weight distribution before and after the scaling is showed in Figure 7.

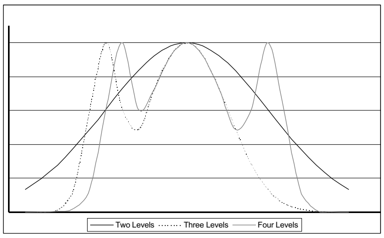

Figure 5. Gaussian distribution of weights

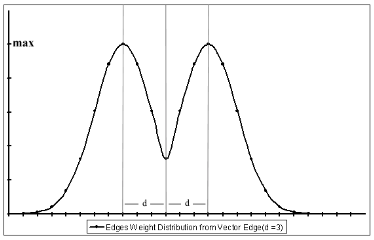

Figure 6. Gaussian distribution of the weight scales

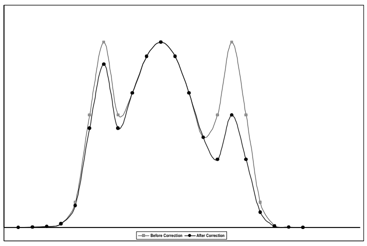

Figure 7. Gaussian distribution before and after the curb correction

Finally, the weight distribution on the axes perpendicular to the vector edge is given by the formula:

$$P(x) = \text{Max } \{K_1(x)*G_1(x),\ G_2(x),\ K_3(x)*G_3(x)\}, \tag{7}$$

where $K_i(x) = Max\{\frac{1}{\sqrt{2ps}_i} e^{\frac{(x-m_{vector}-d)^2}{-2s_i^2}}, \frac{1}{\sqrt{2ps}_i} e^{\frac{(x-m_{vector}+d)^2}{-2s_i^2}}\},\ G_i(x) = \frac{1}{\sqrt{2ps}_i} e^{\frac{(x-m_i)^2}{-2s_i^2}}$

Due to the fact that weights contribute to the calculation of the standard deviation s ?, an equal projection should be established so the s ?'s from different weight distributions result into the same contribution. To incorporate that, all weights are scaled to a range from 0 to 1, by using the formula:

$$P(x) = \frac{P(x)}{\sum P(x)} \tag{8}$$

At this point we should note that for the first three iterations of the least squares solution, all the weights are scaled to a 0.5 to 1 range, so that the whole window is contributing to the solution, and possible edges near the sides of the window are not excluded from the solution.

4.5 Experimental results and evaluation of the performance

4.5.1 Supporting Decision Making. The statistical tools of least squares adjustments provide the mathematical foundation necessary to come with a valid analysis of the obtained results and automatically decide whether change occurred or not. During the execution of the matching loop, several criteria are considered.

First we check for the value of the shift dX. A threshold of 1/10 of a pixel is set to classify a matching as successful. During the application of the DLSM, a significant amount of visually successful matches was not correctly identified, because the value of the shift was not close to our threshold. After examining the behavior of dX during the iterations, several periodicity patterns were detected (Fig. 8). In many cases though these patterns were misleading, since they appear in a high amount of unsuccessful matches. The distinction between a successful match and an unsuccessful one was observed to be the range of dX. If that variation is within one pixel, then it is considered successful, otherwise

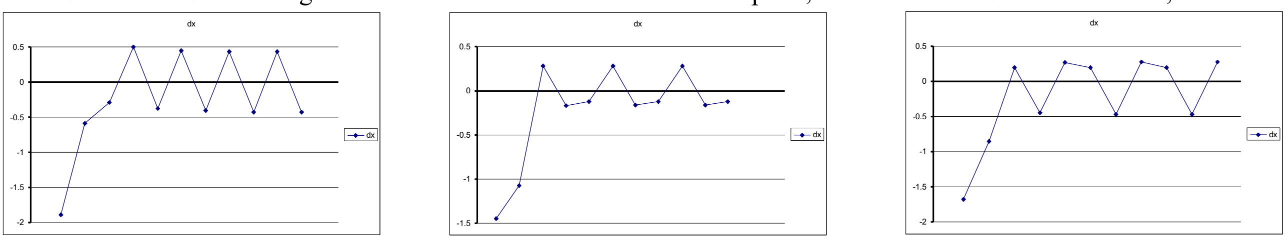

Figure 8. Patterns of dX variations through iterations

rejected. Another statistical tool for the analysis of adjustment results is the a posteriori variance of unit weight. This variance expresses how well the overall model fits to the observations. The variance-covariance matrix for parameters describes the error ellipses of the estimated parameters and was also used to evaluate the matching results.

4.5.2 Sensor Corrections. After the DLSM, new positions for the edges are established. A critical reasoning for our application has to be applied, whether actual change exists, or these deviations are inherited from systematic errors of the source (e.g. misregistration, internal orientation errors). We compare change residuals with directional patterns that describe specific deformations in aerial photogrammetry. Mathematical models that describe these deviations are interpolated between the prior and the new edge positions. A least squares solution provides confidence for the success of the fitting models, and if such models are detected, the relevant metadata in the MIS are updated to help future solutions.

4.5.3 Evaluation of results. In order to test the algorithm's performance a prototype spatiotemporal gazetteer was created of a semi-urban scene (campus of UMaine). Our multimedia sources provide a description of the campus during the last century. The available datasets are aerial imagery, maps, and vector data. From older aerial images we extracted buildings manually, and overlaid them on subsequent raster images. Our main objective was to correctly identify changed areas, and to verify unchanged points. Three factors were considered through the evaluation:

- Good Detection: the ability to locate and mark all the real edges.
- Good Localization: minimal distance between the detected edge and real edge.
- Clear Response: only one response per edge.

Good localization is the major advantage of LSM. Indeed, experiments showed that the extracted edges approximated the real ones at subpixel accuracy (approx. 0.1 pixel). A significant improvement in the performance was noticed when the edge levels were three or more and we were able to establish a geometric representation of the edge. This geometric analysis proved to be very fast, since the weight matrix had to be constructed once for every matching point. The width of the level(s) establishes a scaling factor in the whole process, which guides the template quickly and accurately to the new edge, when there is no change. With this, we achieve good detection, since high accuracy was achieved when edge geometry was incorporated in the solution. Random noise such as building windows, shadows, or cars was initially affecting the algorithm. The *expected* edge geometry analysis allows us to distinguish random noise from the real edge. Especially in the case of shadows, a problem inherently difficult since the artificial edges are very strong, the *expected* geometry of the edge, expressed through the size of the curb, introduced the essential metric reasoning to compensate for such errors. A snapshot of our application environment is showed in figure 9.

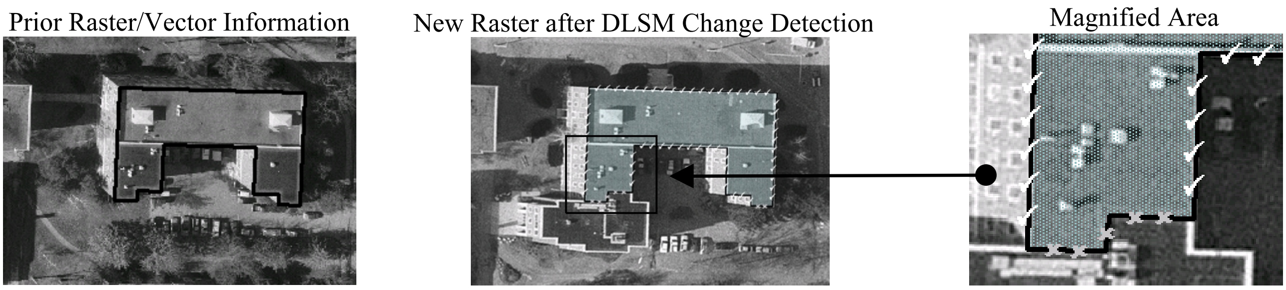

Figure 9. Example of our application environment, where × gives no match, and ✓ successful match

5 CONCLUSIONS

The SpatioTemporal Gazetteer is a suitable vehicle to make explicit the valuable change information that resides over diverse datasets in modern GIS. It allows us to link different object representations from a variety of source types into a single workspace. The combination of the geographic entity register with the other registers provides the ability to navigate through different change resolutions, from the existence of an object to the detailed aspects of change, such as movement, thematic, and boundary reconfiguration.

Within our integrated environment, a major operation is to detect change. In this paper we focus on identifying object outline change in sequences of digital images. The digital image analysis method used is based on least squares template matching. We extent this to function in a differential mode. In doing so, we integrate object extraction from digital imagery with change detection in a single process. By using image orientation parameters and positional data we can reduce the problem of 3-D object monitoring to an image-space 2-D matching problem. Both raster and vector datasets are combined to enhance our solution. Analysis of the edge geometry within a template, before the actual matching takes place, improves the accuracy and reliability of the presented technique. As a post-process, actual change can be distinguished from different representations of the same object due to sensor inaccuracies, through fitting models of known systematic photogrammetric errors.

While our experiments focused on vertical photography, the mathematical foundation of our algorithms would accommodate equally well oblique imagery, even close range photos. We plan to extend our edge geometry analysis technique to include semantic reasoning based on scale space concepts. This will enable us to process efficiently multi-resolutional and multi-scale imagery. The way our process is functioning, each point is matched locally and independently. Our next goal would be to proceed towards an object-wise global solution where solutions along numerous points of the same outline are connected. This would strengthen the solution, by identifying random variations that may appear in the new scene. These variations can be either local, e.g. shadows, or global, e.g. illumination differences or due to different sensor resolution.

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