Towards Spatial Description-Based Integration of Biomedical Atlases

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Abstract. Biomedical imaging has become ubiquitous in both, basic research and the clinical sciences. Technology advances, and the resulting multitude of imaging modalities, have led to a sharp rise in the quantity and quality of such images. Whether for epidemiological studies, educational uses, monitoring the clinical progress of a patient or translational science purposes, being able to integrate and compare such image-based data has developed into an increasingly critical component in the Life Sciences and eHealth domain. Image processing-based solutions have difficulties when the underlying morphologies are too different. Ontology-based solutions often lack spatial precision. In this paper, we describe a compromise solution which captures location in biomedical images via spatial descriptions using so-called fiducial points. The work is discussed in the context of biomedical atlases and includes, in addition to the introduction of the basic method, some experimental performance results.

Keywords: spatial description, integration of biomedical images/atlases.

1 Introduction

Patients are now routinely undergoing a variety of medical imaging investigations, such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scanning, and the images resulting from these investigations become part of the patients' medical records. The same as well as other imaging techniques, e.g. optical imaging, are also used in preclinical studies and the Life Sciences. The work presented in this paper is rooted in the latter and uses examples from biomedical atlases, where we consider an atlas to consist of the image data components, a set of labels describing structures in the images, and mappings between them. There are questions of data integration within the domain of clinical images, within the Life Sciences image datasets, as well as between human and model organism data. The latter being particularly of interest in the translational sciences.

Biologists have access to a variety of biomedical atlases. Many of these atlases are data sources for the same experimental field, for example, mouse gene expression data. Though storing the same type of data, different experimental designs, varying analysis of results and different update routines have caused the data in these atlases to be different. The consequence is that these atlases may provide

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different results even for the same query. It is vital that multiple resources in the same field are used so that full and complete results can be generated for the query. The comparative clinical issue is the integration of different medical images for a single patient, or the comparison of images of multiple patients with the same disease.

A biomedical atlas consists of a graphical model, the ontology associated with the graphical model and a mapping between these two. The ontology contains a collection of anatomical domains and relations between these domains. The graphical model is the image for a mammalian with those anatomical domains. This paper proposes the integration of these data sources by mapping the images of biomedical atlases using spatial descriptions. Given two images $I1$ and $I2$, mapping one image onto another means that, for each anatomical space in image $I1$, we try to find a corresponding space, which has the same intended meaning, in image $I2$. For this study, we circumvent the extra complexity of image segmentation by considering anatomical domains that can be easily segmented. More specifically, we explore 2D image space of mouse embryo domains.

Mappings anatomical spaces concern a number of issues. Different images may have a different number of segmented regions causing one structure to correspond to parts of several structures, and vice versa. Furthermore, even if these images may have the same anatomical structures, the morphology may vary with scale, orientation and the position of the structure. In addition, different biomedical atlases may have the same segmented images but may use different anatomical names causing interoperability issue of finding correspondences anatomical regions between these images. An efficient representation structure is necessary to conceptualize anatomical space of an image to guide the mapping process. This paper explores spatial description-based approach for the linking of images for the integration of biomedical atlases.

Section 2 presents an overview of image mapping approaches. The proposed integration approach is described in Section 3. Section 4 provides experimental results of the proposed approach. In Section 5, a discussion is presented. Finally, a conclusion in Section 6.

2 An Overview of Image Mapping Approaches

This section discusses two approaches for mapping. In particular, its focus is on the following approaches: (1) ontology based mapping (2) image processing based mapping. Ontology based mapping depends on spatial relations between anatomical regions, whereas, mapping using image processing depends on fiducial points.

2.1 Spatial Relations: Ontology Based

This section describes the mapping between anatomical spaces across images using ontologies. Mappings based on an ontology start by segmenting the image of a biomedical atlas according to its anatomical regions. Subsequently, the regions can be linked to the appropriate concepts in the atlas' anatomy ontology. Two regions are then mapped according to the similarity of their spatial relationships. Given two atlas anatomy ontologies O_1 and O_2, if anatomical structure A_1 in ontology O_1 has the relationships A_1 is adjacent to B_1, and A_1 is adjacent to C_1 then its equivalent anatomical structure, A_2, in ontology O_2, must be adjacent to B_2 and C_2, where the latter two correspond to B_1 and C_1, respectively. The integration of biomedical atlases can then be achieved by linking between their respective anatomy ontologies.

The concepts of spatial relations have been well employed in ontologies by both FMA [1] and Bittner et al. 2008 [2] to describe anatomical space in the biomedical domain. In general, spatial relations between anatomical entities are described using relationships from the following categories:

Mereological relations describe the concept of parthood between the whole and its parts, e.g., finger is *part of* hand, hand is *part of* the arm etcetera.

Topological relations describe the concept of adjacency, discreteness, and connectedness among entities. Two entities are described as being *adjacent* when they are close to each other, but not connected. *Discrete* entities are not connected. If two entities have a common anatomical space, such that they partially coincide or are externally attached with one another, they are said to be *connected.*, e.g., two entities are externally connected if the distance between them is zero and do not overlap, for example, in human major parts of the joint, the synovial cavity is externally connected to the synovial membrane [2].

Location relations describe the concept of relative location between entities that may coincide wholly or partially without being *part of* one another, for example, the brain is located in (but not *part of*) cranial cavity.

Based on spatial relations, for example, anatomical region x in Figure 1(a) is mapped to the result region y in Figure 1(b) if x is described as:

'adjacent(x, midgut), adjacent(x, liver)'

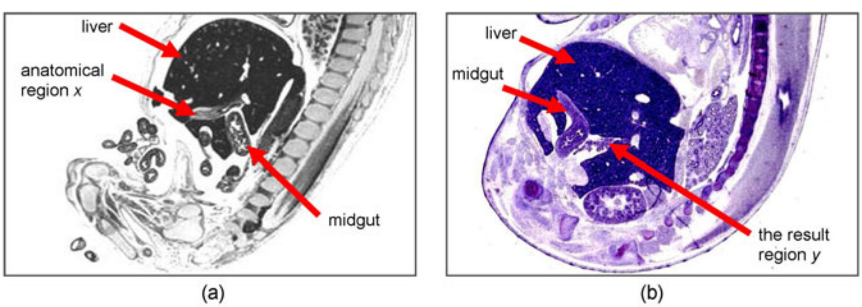

Fig. 1. Based on spatial adjacency between (a) anatomical region x with other anatomical regions will map x to (b) the result region y

2.2 Fiducial Points: Image Processing Based

This section discusses the mapping between biomedical atlases based on image processing techniques. These methods start by examining the pixels in an image to classify them into regions, e.g. [3,4]. Classification is by the pixel's intensity level. Subsequently, a registration algorithm is required to identify equivalent regions, across images, based on pixels. In addition, based on the pixel classification, fiducial points can be located. A fiducial point is a point in space in either 2D or 3D, typically an anatomical landmark which is easily recognizable in an image, usually identified by human experts and possibly assisted by auto/semi-automated image processing algorithms. These fiducial points are typically used for registration experimentation image of canonical atlas. Izard and Jedynak [5] describes a registration approach which employs a Bayesian model to detect these points in order to map between regions across images. Registration technique as proposed by Khaissidi et al. 2009 [6] uses the Hough Transform algorithm to align medical images, based on fiducial points extracted from the two compared images. However, the drawback of image processing based mapping in general is that it has the possibility to fail if there is a large variation in pixel/voxel intensity [7].

3 Concept of Spatial Description

3.1 Spatial Description Based on Fiducial Points and a Set of Spatial Relations

The proposed approach of mapping involved the concepts of a query region, fiducial points and fiducial lines. A fiducial point is a point in space. A fiducial line is made up by creating a straight line through a pair of fiducial points. A query region is made up of connected multiple single-elements within a closed boundary. Given two images *I1* and *I2*, mapping one image onto another starts by selecting the same fiducial points in both images. We then describe a query region using spatial relations between the query region with respect to the fiducial points. Two regions from different images are then mapped according to the similarity of their spatial description. For example, if query region *X* in image *I1* is described as *X is north of fiducial point P1* and *X is west of fiducial point P2*, then its equivalent region in image *I2* must be a region that is located north of fiducial point *P1* and west of fiducial point *P2*. Figure 2 depicts the framework of the approach. The image processing based mapping inspires the idea of using fiducial points. Because a fiducial point can become a point of reference for an anatomical location, this paper intends to describe a query region based on these points using spatial relations. The idea of using spatial relations, on the other hand, is inspired by ontology based mapping. Because a spatial relation can describe the location of a region in space, this paper proposes to describe a query region using fiducial points and a set of spatial relations. By the use of spatial relations, this approach works independently of image pixel/voxel intensities.

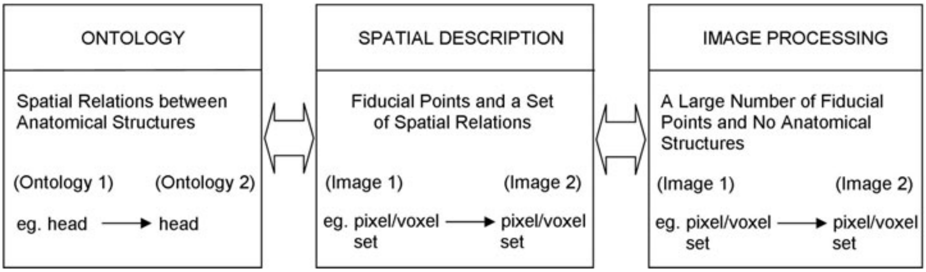

Fig. 2. Ontology-based mappings align images by identifying correspondences among elements of two ontologies based on spatial relations between anatomical structures. The image processing based mappings align images based on equivalent pixel/voxel intensities corresponding the fiducial points

On the other hand, the use of fiducial points allows this approach to work independently of spatial relations between segmented regions. The approach does not intend to include a large number of concepts in spatial relations as that replicates the ontology mapping approach. The entire spatial area of an image should be conceptualized with a small number of fiducial points such that the attempt is not a replicate to the image processing mapping approach. We now summarize the formalism of the approach. We define directional relations as

$$D = \{northOf, eastOf, southOf, westOf\} \quad (1)$$

We describe a query region x in an image as

$$S_Q = \{r(x, f_i) \mid r \in D \text{ } and \text{ } f_i \in (F_{point} \cup F_{line})\} \quad (2)$$

where S_Q is the spatial description for query region x with respect to a fiducial point $F_{point} = \{p_1, p_2, \ldots, p_n\}$ or a fiducial line $F_{line} = \{l_1, l_2, \ldots, l_n\}$

Figure 3 depicts two images of mouse embryo with 6 fiducial points and 15 fiducial lines. The simplified description for query region X is described as:

'southOf(X, P6P2), eastOf(X, P1P4), northOf(X,P2P5), westOf(X, P1P3)'

Note that, in the description, we label a fiducial line according to its pair of fiducial points. The location highlighted in Figure 3(b) denotes the matched location corresponding to the description.

4 Experimental Results

A series of experiments were conducted to demonstrate how fiducial points and a set of spatial relations can be used to describe locations. For the experiments, an image representing the mouse embryo was used and 102 spatial regions were annotated in the image. The image generated 97104 query regions each of size

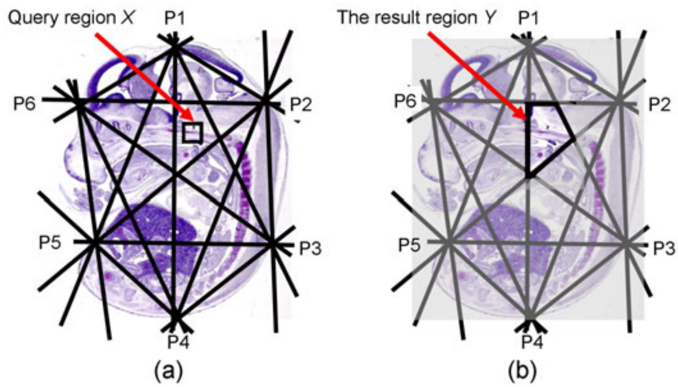

Fig. 3. Spatial description based on fiducial points and a set of spatial relations maps (a) query region X to (b) result region Y

50x50 squared pixels, 68154 query regions each of size 100x100 squared pixels, 44204 query regions each of size 150x150 squared pixels, and 25254 query regions each of size 200x200 squared pixels. For all query regions of size 50x50 squared pixels, the first query region starts at the top-left corner of the image and is increased every time by one pixel in order to generate the following query region and so on. Query regions of other sizes are also generated by following this step of one pixel. The idea of using query regions is to test the mappings of pixels in a query region of one image to pixels in a region of another image based on fiducial points. The percentage of accuracy is calculated by dividing the total number of pixels in X by the total number of pixels in result region Y, and multiply by 100 (see Figure 3). Figure 4(A) depicts the average percentage of accuracy served by number of fiducial points. Results show that the more fiducial points

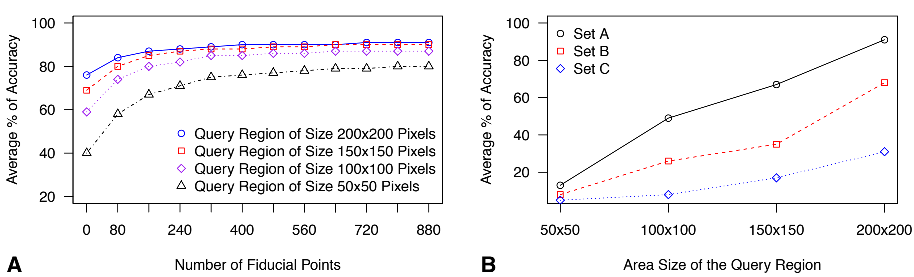

Fig. 4. (**A**) Average percentage of accuracy served by number of fiducial points. The more fiducial points are included the higher the average percentage of accuracy gets. Moreover, the average percentage of accuracy substantially increases as the query region area size gets larger. (**B**) Average percentage of accuracy in three different positioning sets of 8 fiducial points served by query region area size. The same number of fiducial point place at different positions produce different average percentage of accuracy.

were included, the more accurate the mapping was. In addition, the mapping accuracy substantially increases as the query region area size gets larger. Fiducial points provide qualitative spatial relations to describe locations. Therefore, the more fiducial points are used the more spatial relations are available to describe locations, which increases the average percentage of accuracy. In general, spatial descriptions will return a location which is either larger or equal to the actual area location. Thus, for cases where spatial descriptions for the corresponding query regions do not return locations that are exactly equal to the actual location, the larger the size of the query region, the more accurate it is to the actual area, by which contribute to much higher accuracy value compared to the smaller one. Figure 4(B) depicts the average percentage of accuracy in three different positioning sets of 8 fiducial points served by query region size. Results show that the same number of fiducial points placed at different positions produce different accuracy. The positions of fiducial points determine spatial relations made available to describe locations. Because the location is determined by spatial descriptions, different positioning set for the same number of fiducial points certainly contributes to different spatial descriptions to describe locations, which produce different average percentages of accuracy. Overall, with the appropriate number of fiducial points used and better selection of fiducial point location, mappings can be improve in terms of accuracy.

5 Discussion

The definition for best match criteria is important in any mapping algorithm. Because anatomical structures exist at different range of scale, arrangement and the position, there is a possibility for an exact copy of location corresponding the query region in one image to be unavailable in another image. The proposed spatial description approach at the current state perform mappings by returning a location that satisfies all spatial relation constraints corresponding to a query region. However, this may not be necessary. Therefore, the google-style matches can be considered. This can be done by specifying a range, for example, allowing for a distance limit from a fiducial line, which will return a location given by the range.

A preliminary experiment has also been conducted to compare the performance of spatial descriptions based on fiducial points and a set of spatial relations with the following approaches: (1) spatial description based on spatial relationships between segmented regions (2) spatial description based on fiducial points and a set of spatial relations, integrated with spatial relations between segmented regions. Experimental results verified that mapping using spatial description based on spatial relationships between segmented regions managed to produce better accuracy compared to spatial description based on fiducial points and a set of spatial relations. However, this result cannot be used to benchmark the overall mapping performance produced by spatial description based on fiducial points. Depending on better selection of fiducial point locations or by increasing the number of fiducial points used, the mapping accuracy can be further increased. Furthermore, experimental results have verified that the approach of mapping using spatial description based on fiducial points and a set of spatial relations, integrated with spatial relations between segmented regions can yield significantly higher mapping accuracy compared to using either approach alone.

6 Conclusion and Future Work

This paper explores spatial description based approach to facilitate data integration across biomedical atlases. The most important feature of our approach is that the spatial description, which is rule-based, can provide the means to facilitate the mapping between images of biomedical atlases. Future work includes research on selection of fiducial points where the combination can give performance, as effective as both ontology-based and image processing algorithm; and analyse the capability of spatial description to facilitate data integration between (1) images (i.e. from biomedical atlases), (2) natural-language description of space (i.e. free text from biomedical literature) (3) database warehouses (i.e. structured database of biomedical facts).

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