MARKERS DETECTION BASED ON THE DISPARITY ANALYSIS

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ABSTRACT

The image registration is defined as a searching for the best geometric transform, which describes the relationship between the reference image and the floated image. There are two approaches how to register corresponding images. The main difference is in the geometrical transform applied to the floated image. Mostly we use the global parameters, but in the area of soft tissue movements (e.g. muscles) the global geometrical transform is inefficient, thus the local geometrical transform has to be applied. The registration is then based on a number of corresponded markers, which have to be found in both images.

1. INTRODUCTION

As mentioned in [1], the disparity analysis is usually used for the reconstruction of spatial objects or scenes based on stereo images sequences, detection and evaluation of temporal developments of spatial relations. Disparities are usually determined with pixel accuracy. When r_A, r_B are position vectors of a feature present in both images A and B, the two-dimensional difference vector $\Delta r = r_A - r_B$ is usually denoted as disparity at r_B. The required number of correspondences starts from a few for simple orientation task and rigid geometrical transform and increase to several tens for global flexible transforms. In the latter case of a dense set of disparities among which it may be further interpolated, the resulting spatial function $\Delta r(x,y)$, or in discrete representation $\Delta r_{i,k}$ is called the disparity map. It is usually utilized as the input for a higher-level analysis, e.g. estimation of motion or for three-dimensional surface determination or scene reconstruction in stereo analysis. The set of points in the base image, for which the correspondences are to be determined, is given either by preliminary determined prominent features (edges, corners, crossings, singular point objects, etc.) or by regular grid of an a priori chosen density, regardless of the image content.

2. CORRESPONDENCES BASED ON THE REGULAR GRID

This approach eliminates the difficult and unreliable phase of features detection as well as the following complex determination of valid correspondences. The patterns to be found are simply small areas around the node points in image B. However, nothing is a priori known on the corresponding areas in A except that these areas may be expected in a vicinity of the respective node points in A. This approach relies on local patterns and textures in both images being adequately similar in corresponding areas, while at the same time being sufficiently diverse in other image areas not to allow confusion of the similarity criterion. In every case, the fundamental problem of disparity analysis reduces to precise determination of the vector r_A in image A corresponding to known position r_B in image B. A defined area (usually square), surrounding the node point r_B in image B, carries the pattern to be found in image A. By shifting the pattern as a mask on image A in the vicinity of $x_A = r_B$, the best match of local content of image A with the mask pattern is found at point r_A. The optimum disparity $\Delta r = r_A - r_B = (\Delta x, \Delta y)$ is thus determined for the point r_B. The match is optimal in the sense of the chosen similarity criterion; therefore, finding a single disparity is an optimization problem. Besides the choice of similarity criterion, the size of the area taken as patterns and the extent around x_A, in which the pattern is searched. Usually, the images subject to disparity analysis are provided by a single modality, or both may be preliminary formed as vector/valued images obtained by fusion from more modalities. Therefore, usually the intensity/based similarity criteria are used, e.g. angle criterion [1].

2.1. THE LEVEL APPROACH OF THE DISPARITY ANALYSIS

As for the mask size, it is obvious that the greater the area, the less is the probability of finding an improper correspondence due to a seeming similarity. On the other hand, a large area may cover a region with different disparities. This may preclude similarity recognition and, when it is at all recognized, obviously worsens the disparity resolution. The second parameter is no less critical: too large a search extent may lead to finding a distant false correspondence due to an accidentally higher seeming similarity than the proper one. Too small a search extent may have paradoxically the same result as the pattern may be included in the searched area only incompletely. Both parameters thus influence the reliability of found correspondence. Moreover, they obviously influence the computational requirements. [1] The level approach of the disparity analysis results in an improvement in the sense of more precise process of searching for the correspondences based on a sequential downsizing of the mask and the extent.

Figure 1: Global position of the mask (white border)
Left: level1 (mask = 31px, extend=41px), Right: (mask = 19px, extend=23px)

2.2. THE DISPARITY MAP CORRECTION

As mentioned in [1], although the mask is found on the right coordinates based on the texture, the scene might be changed before the second acquisition in the sense of increase. This may happen in the area of soft tissues (muscles, etc.). This kind of wrong disparities is similar to the meaning of the impulse noise (salt and pepper), where pixels (mask positions) in the image are very different in intensity (values of shift) from their surrounding pixels (mask positions). To eliminate these very different values of shift, two problems need to be solved:

1. How to detect the false pixels
2. How to calculate a suitable substitute

The automatic false shift detection may be based on artificial intelligence methods that would also take into account the contextual information, probability description, etc. Among some typical criteria of inconsistency belongs the Limit on the sum of absolute differences:

$$\sum_j \sum_l \left| f_{i,k} - f_{i+j,k+l} \right| > S, \qquad (j,l) \in A, \qquad (1)$$

where A defines the considered neighborhood of usually a constant number N of shifts.
The limit S determines the sensitivity of the detector

The false shift values are consequently to be replaced with shift values interpolated somehow from a neighborhood that may be similarly shaped as the detection neighborhood. The simple possibilities of the estimation are:

- The nearest unaffected neighbor
- The average of the neighborhood, not including the false shift values
- Interpolation from the unaffected neighboring pixels (linear, bicubic, etc.)

2.3. THE VISUALIZATION AND COMPARISION OF THE CORRESPONDENCES

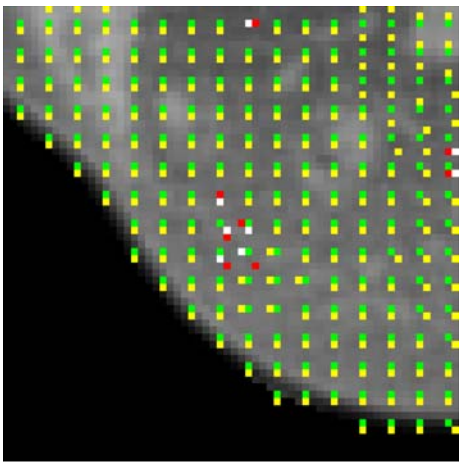

Figure 2: The detail of the disparity analysis: reference points (green), founded (yellow), wrong (red) and corrected correspondences (white)

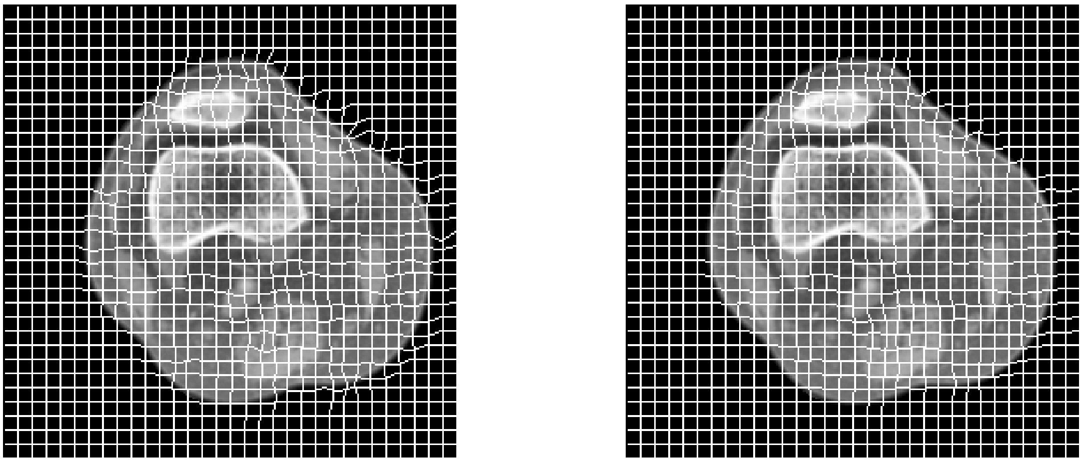

Figure 3: The visual comparison using a grid deformation (right: after the correction)

3. CONCLUSION

This method was tested on a set of corresponded pre-contrast and post-contrast CTA scans acquired from the patients' knee area. These images are saved in the Dicom file format and before testing, they were preprocessed (artifacts were removed; the adaptive equalization was used to the contrast enhancement, etc.). The results were compared manually. This approach gives good results in determining of local parameters used then for the 2D image registration, but it can be improved also for the 3D application.

REFERENCES

[1] JAN, J. *Medical Image Processing, Reconstruction and Restoration - Concepts and Methods.* Boca Raton, FL, USA: CRC Press, Taylor and Francis Group, 2005. 760 s. ISBN: 0-8247-5849-8.