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Mapping Grey-Levels on 3D Segmented Anatomical districts

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Abstract

The study aims to perform a simple but effective integration of geometric information of segmented 3D bones' surface and density information provided by volume MRI (Magnetic Resonance Imaging). Such a representation method could support diagnosis process, biomedical simulation, computed assisted surgery and prosthesis fitting. The input consists of a volume MRI of a carpal district and the corresponding 3D surface model. The algorithm superimposes image and surface, and, once found the image voxel correspondent to each surface point, maps the grey level of the voxels identified on the segmented surface. The output is a surface mesh on which the texture, induced by the MRI, has been mapped. The approach is effective, general and applicable to different anatomical districts. Further elaboration of the results can be used to perform landmark identification or segmentation correction.

CCS Concepts

• ***Computing methodologies*** → *Grey-levels mapping;*

1. Introduction

In radiology, a huge part of the diagnosis process relays on the support of imaging exams like CTs or MRIs that, nowadays, are capable to provide 3D representations. Moreover, Computer Graphics algorithms can build accurate 3D models, describing the surface characteristics of the selected organs or tissues. In this way, surgeons and physicians have a better view of anatomical districts, helping them in early diagnosis of different kinds of illnesses, surgical intervention, prosthesis project, physiotherapy planning, and so on. In radiology, physicians can rely on the support of instruments that analyse the 3D surface model reconstructed from the input images or to process them to extract quantitative parameters. A 3D surface model provides information about the patient-specific shape of bones and ligaments [HM09], [BCPS16], but lacks of the information about volume characteristics given by the medical image. A volumetric medical image, depending on the scanning system, can provide density and anatomical information or else chemical and metabolic ones. Thus, through segmentation [CFTV11], and processing [Ban08], it is possible to isolate the region of interest for further analyze it. On the other hand, image processing and analysis are not as accurate as shape analysis in performing geometric evaluations. The purpose of this study is to understand if a simple integration of these two points of view could introduce an effective improvement in the representation of the bones and articulations. Using 3D low field MRI, of the carpal area, and the 3D surface meshes derived from the MRI segmentation, the algorithm performs integration of surface based and volume based information, providing a comprehensive visualization of both geometric and density characteristics. The innovations offered by this method reside in its simplicity, effectiveness and generality. It is, indeed, applicable to other anatomical districts or type of images. This study has been used as a visualization method but, in future, we plan to validate it in collaboration with medical doctors.

2. Proposed approach

The dataset, used for this work, was provided by Softeco and was composed of 112 patients' 3D MRI images of the carpal district, the relative 112 segmentations performed by experts in the field and the corresponding 3D mesh models obtained from the segmentation. To integrate surface-based (i.e., the 3D bone representation) with volume-based (i.e., the MRI grey levels) information we mapped appropriate grey levels of the MRI scan onto the surface of the bone. As input, we considered the raw 3D MR images and the relative patient-specific surface models, obtained from the segmentation of the corresponding MRI. The volume images were constituted by a series of slices, and each slice is a 256×256 image. The whole series constituted the acquired volume of the carpal district. The MR images and the 3D segmentation were processed in order to superimpose them and to find the correct correspondences between one and the other.

Surface-volume correspondence The surface mesh, of the segmented bones, consists of a set of vertices, each vertex has coordinates: $p_i = (x_i, y_i, z_i)$. The 3D volume image, instead, consists of voxels ordered with indexes, and the dimensions of the voxel in each direction are associated with the image metadata. In order to superimpose the mesh models with the image volume, we had

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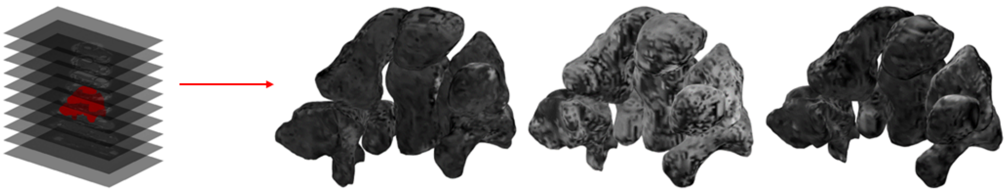

Figure 1: *Result of the mapping approach using, from the left to the right: the distance from the normal toward the exterior of the bone, toward the interior of the bone and the euclidean distance to find correspondence*

expressed the volume with 3D coordinates. To do so, we have created a grid of the same dimensions of the whole volume image and whose elements had the exact dimensions of a single voxel. Since the models were obtained from the images, they share the same reference system. Hence, positioning the bottom left front corner of the grid in the origin of the reference system, volume and surface resulted superimposed. The second step consisted in identifying which of the volume voxel was the one corresponding to a vertex. We defined as voxel corresponding to a vertex, the one nearest to it. In order to try different modalities we used two definitions of distance. The first one is the Euclidean distance:

$$(p_i, v_j) = \sqrt[2]{(p^x{}_i - v^x{}_i)^2 + (p^y{}_i - v^y{}_j)^2 + (p^z{}_i - v^z{}_j)^2},$$

where p_i refers to the $i-th$ vertex of the surface, and v_j the $j-th$ node of the 3D volume grid. The second one is the distance from the normal to the surface on the vertex considered, in this way we were able to decide whether to look inside or outside the selected bone. A positive dot product between the surface normal on the vertex and the vector connecting the vertex to a node indicates a node outside the bone, while a negative one a node inside the bone's surface. We looked in both directions separately: inside and outside the bone. The distance considered in this case was:

$$d(p_i, v_j) = \frac{\|\mathbf{n} \wedge \mathbf{e}_{ij}\|}{\|\mathbf{n}\|},$$

where $\mathbf{n}$ indicates the normal to the surface of the selected vertex and $\mathbf{e}_{ij} = \mathbf{p}_i - \mathbf{v}_j$ the vector connecting the vertex to the node. For each mesh vertex, scanning the whole volume, we find the nearest volume voxel (i.e. the one with minimum distance from the vertex) in the sense of the two distances considered above.

Gray level mapping At this point, every vertex on the surface of the bone has been associated with the corresponding voxel of the volume. Moreover, each vertex of the mesh belongs to a triangle. In order to perform the actual mapping, we coloured the triangle of the considered vertex of the same grey level owned by the correspondent voxel. (Fig. 1).

2.1. Results and discussions

The method supports the integration of the surface shape model with the image volume grey levels and increases the information that such a representation can provide to physicians and surgeons. Having the information about bone density added to shape characteristics can overcome the limits of methods that are based exclusively on volume processing. From a first analysis, this mapping performs as expected. The surface results clearer if the direction of the search is addressed toward the interior of the surface, where the bone marrow is placed. Contrarily, looking outside the bone surface the predominant tissues are cortical bone, ligaments, and cartilage, thus less dense structures which appear darker in the MRI acquisition. Thus, an example of possible application regards degenerative illnesses: this representation could underline regions where the bone has been eroded. In fact, regions that previously were brighter, in a second time could result darker, meaning that the bone tissue has been replaced by cartilage tissue. The Euclidean distance does not distinguish between inside or outside the bone, indeed, the mapping results less smooth. This pipeline is quite general and is straightforwardly applicable to other anatomical districts. The representation method can support the possibility to track illnesses progression in time, as well as to compare one patient with others: from 3D models, it is possible to assess morphological changes of the district, while 3D volume images provide information about the tissues damaged by the pathology. This kind of comparison can result extremely effective in diagnosis and follow-up of degenerative pathology. Starting from this integrated visualization, future developments include the actual application to landmark automatic recognition and segmentation correction. Given the integration of information obtainable by the visualization method developed, automatic identification of patient-specific ligament insertion could be of high interest. Ligaments, in fact, present different density if compared bones, thus they should be identified by different grey level in the 3D image volume. On the other hand, low field MRI has not the resolution necessary to immediately identify those regions. We hope that the combination of image grey levels and shape characteristics could compensate for this lack in image resolution, opening the possibility of performing ligament insertion identification.

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