3D models from unpositioned range images

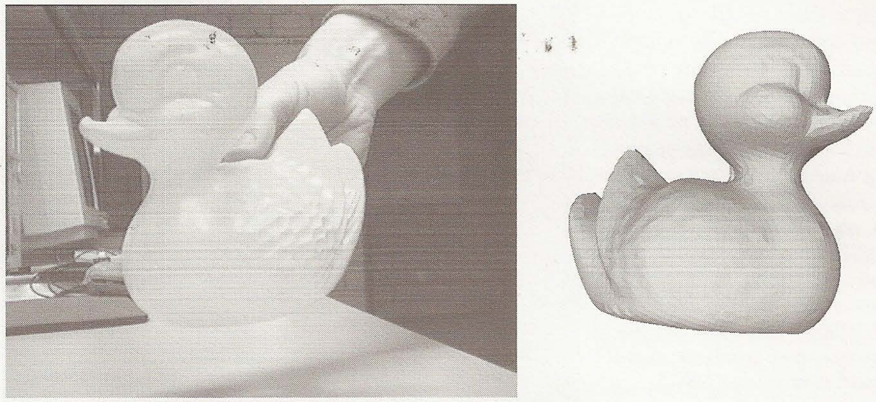

Figure 1. A real object becomes virtual.

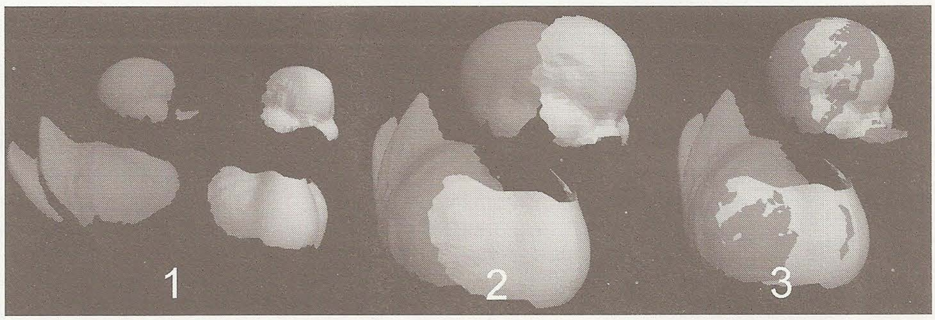

Figure 2. Range view registration by geometric matching.

The increasing use of virtual objects for various applications like multimedia, reverse engineering, object recognition, etc. calls for effective means for creating virtual representations from real objects (Figure 1). This modeling task basically requires us to measure the geometry of the object and to transform these measurements into a suitable virtual representation. The purpose of this article is to briefly review the modeling process and, more particularly, to show that introducing matching techniques during the transformation phase allows us to get rid of range view positioning during the acquisition phase.

A wide variety of 3D scanners is available for the measurement of object geometry. Laser scanners typically use the principle of triangulation between a laser beam and an imaging camera to provide a range profile or range image. Structured light scanners use the triangulation principle between some projected light pattern and an imaging camera. Auto focus scanners derive the depth from the focused image distances. Today, range scanners are the most important type for modeling because they provide fast and dense measurement of object-camera distances in the form of range images. A range image is also called a range view because it provides a map of object geometry as it is observed from a given orientation. Because of the nature of real objects, several range views are required in order to measure the geometry of the full object.

Once a complete set of range views is available, the effective modeling can start. The main task is to assemble these views into a unique and final representation. Typically, this is done in a so-called fusion process, which aims at linking the various measurements into a mesh structure that is suited for a surface representation. This view-assembly task is quite straightforward if the object is positioned for each view of the acquisition, which means that the object is moved in a well-known coordinate system with respect to the camera. Thus, it presupposes the presence of an accurate positioning system used to measure each pose change of the object and the scanner.

With the geometric matching approach[1-3] a solution is provided that allows us to model objects from *a priori* unpositioned views: the object acquisition process delivers a set of range views whose respective poses remain unknown. The advantage is that the range views can be recorded without expensive positioning devices. Also, scanning occurs without any positioning constraints and any view can be freely chosen. It is a solution for all cases where positioning is not available or impossible. It is also a solution where positioning must be very flexible. Finally, it is a solution where the positioning is not accurate.

The basic idea of the geometric matching approach to object modeling is to take advantage of the intrinsic geometric properties of neighboring range views in order to register them. It is assumed that the views have some overlap such that descriptions of a common part can be used for view registration. The implementation of this idea requires that we add a registration stage to the modeling. During this phase the available views are successfully matched and then directly fused in a way that is similar to the standard modeling method. Figure 2 illustrates how two single views are brought into registration by the iterative geometric matching procedure. The computational complexity of this solution is now known to vary very widely depending on the context of the application. Different contexts will lead either to interactively assisted registration or to fully automated solutions.[4,5]

Besides geometry, object appearance is also important. 3D models do not look realistic if

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Classification of skin tumors

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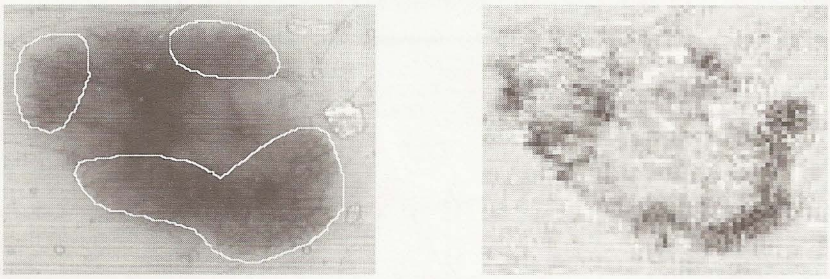

Figure 2. a) Image of a benign tumor with areas labeled as "pigmented network" by dermatologists, and b) its interpretation by the classifier (right panel) ("pigmented networks" correspond to dark areas).

supervised. A generalized Hebbian algorithm operates principal-component-like analysis of windows randomly selected within these specific sets. Primitive windows fitted to various contexts, each of them being appropriate for the description of some aspects of the images (contrast, color, texture, border ...) are consequently obtained.[4] They will be used afterwards to code the windows to be classified. The supervised learning phase required for the construction of the third stage also makes use of the various sets of windows. The target is set following dermatologists' instructions regarding the presence of the features of interest.

Results

Our approach has been applied to the detection of "pigmented network" areas. This feature is characterized by grids of pigmented lines standing out against a lighter background (Figure 2a). The overall percentage of well-classified windows is about 90%. When applied to the analysis of whole images of black tumors, a new image is obtained where areas with the relevant feature are enhanced (Figure 2b). Homogeneous areas, whether dark or light, do not generate any signal. However, in the example given in Figure 2, an artifact resulting from a lack of "oil" (quite frequent in dermatoscopic images) is recognized as a pigmented network area. As a matter of fact, a crucial point when dealing with a learning system is the ability of the learning database to represent the data. In the above situation, it is clear that the database that distinguishes "pigmented network" areas from the "rest of the world" needs to be enriched with artifact examples to improve the accuracy of classification.

Conclusion

Preliminary results dealing with the detection of several features of lesions have been encouraging. However, some basic steps such as finding a truly representative learning databases and well-designed coding scheme have been found critical and do require attention from both medical and technical points of view. Our next step concerns the analysis of color inhomogeneity and tumor asymmetry (spatial distribution of features). We are considering using a very similar approach, based on learning by example, to deal with the detection of these features.

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References

1. R. J. Friedman, D. S. Rigel, and A. W. Kopf, *Early detection of malignant melanoma : The role of physician examination and self-examination of the skin,* **Ca-A Cancer J Clinicians** (35), pp. 130-151, 1985.
2. M. Püspök-Schwarz, A. Steiner, M. Binder, B. Partsch, K. Wolff, and H. Pehamberger, *Statistical evaluation of epiluminescence microscopy criteria in the differential diagnosis of malignant melanoma and pigmented basal cell carcinoma,* **Melanoma Research** (7), pp. 307-311, 1997.
3. K. Wolff, M. Binder, and H. Pehamberger, *Epiluminescence microscopy: a new approach to the early detection of melanoma,* **Adv. Dermatol.** (9), pp. 4556; discussion 57, 1994.
4. S. Haykin, **Neural networks: A comprehensive foundation,** Macmillan College Publishing Company, New York, 1994.

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only their geometrical aspect is taken into account, so color is essential to create a realistic model of an object. Realistic appearance is obtained by assigning either a color or a subimage to each mesh of the model, leading to either a colored or texture-mapped model. The color modeling and the related capturing of the real object color information by physical devices requires that special care be taken to correctly map the texture[6] or to eliminate the unwanted effects of light reflection.[7]

Many applications could benefit by using modeling from unpositioned range images. Among general applications like multimedia, reverse engineering, object recognition, and quality control, the approach is of most interest for those where view positioning is difficult or inconvenient during the acquisition. Portable scanners and archeology are typical examples of these. Very difficult positioning problems are encountered when measuring objects in the micrometer or submicrometer range, and our approach should help with data processing at this scale.

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References

1. P.J. Besl and N.D. McKay, *A Method for Registration of 3D Shapes,* **IEEE Trans. PAMI 14** (2), pp. 239-256, 1992.
2. G. Blais and M. Levine, *Registering multiview range data to create 3D computer objects,* **Proc. IEEE Trans. PAMI 17** (8), pp. 820-824, 1995.
3. Christian Schutz, Timothee Jost, and Heinz Hugli, *Free-form 3D object reconstruction from range images,* **Proc. Int. Conf. Virtual Systems and MultiMedia,** pp. 69-70, August 1997.
4. Heinz Hugli and Christian Schutz, *Geometric matching of 3D objects: assessing the range of successful configurations,* **Proc. Int. Conf. Recent Advances in 3D Digital Imaging and Modeling,** Ottawa, Canada, pp. 101-106, 1997.
5. C. Schutz, T. Jost, and H. Hugli, *Multi-feature matching algorithm for free-form 3D surface registration,* **Proc. ICPR '98,** pp. 982-984.
6. Timothee Jost, Christian Schutz, and Heinz Hugli, *Modeling 3D Textured Objects by Fusion of Multiple Views,* **Proc. EUSIPCO '98 2,** pp. 1073-1076.
7. T. Jost, C. Schutz, and H. Hugli, *Color digitizing and modeling of free-form 3D objects,* **Proc. SPIE 3640,** pp. 38-48, January 1999.