Integrated Shape Model from Multiview Range Images

Takeshi Masuda,* National Institute of Advanced Industrial Science and Technology (AIST), Japan

1 Introduction

To obtain a shape model from partial 3-D shapes measured from multiple directions, it is necessary to solve three problems: 1) matching, 2) registration and 3) integration. Traditionally, these problems have been solved separately, and applied sequentially in this order because of the dependencies among these problems. This is possible if it is assumed that mismatches like false measurements or wrong correspondences can be detected beforehand, but practically, this is not always possible due to complex sensor characteristics. Consequently, the data need to be registered in advance to detect mismatches automatically by comparing multiple views, which arises another dependency.

We proposed a unified framework within which these problems can be solved together[Masuda 2003]. In this framework, object shape is represented by the *signed distance field* (SDF). We represent an SDF sample by a set of signed distance, closest point and surface normal from a 3-D sampling point to the object surface. The input range images are assumed to be roughly registered in advance. They are integrated by a robust estimator that detects mismatches as outliers as well, and then input images are registered to the integrated shape. These two complementary processes are alternately iterated until no additional registration is necessary. Because each input image is registered to the integrated shape, there is no accumulation of alignment error like pairwise registration methods. From the integrated SDF, we can easily reconstruct the object surface attached with surface normals that enables smooth rendering (cf. `hyp3.mpg` for overview of the algorithm).

2 Application on a Large Dataset

This algorithm requires a large volume of memory to store SDFs of input data samples and of the integrated shape. We used a linear octree implemented by a hash function with interleaved integers. For example, an integer coordinate $(3,4,5)$ is interleaved in a binary integer $1\,110\,001\,101_2$. This hash function represents an octree because the parent key is given by shifting out the last 3 bits. We store only the SDF samples that is closer to the input or integrated surfaces than a threshold ($= 2\delta$ in experiments, where δ is the voxel size). The sampling region is a cube whose size is $W = 2^s\delta$, where s is a positive integer representing the sampling level.

The proposed algorithm requires the voxel size δ specified by the operator. This directly determines the resolution of the integrated shape model, but this is also related to the convergence of the registration process. The larger δ is, the larger initial misalignment can be resolved, the more tolerant the process is to local minima, the less computational cost is with less samples. Sequential refining the sampling levels is considered to be taking a coarse-to-fine approach, and this is efficient for treatment of a large dataset.

We applied the proposed method on the data of the Great Buddha in Kamakura Koutokuin measured by the University of Tokyo with a time-of-flight range sensor. This data set consist of 12 triangulated surfaces, which are pre-registered in about a few centimeter accuracy. We set the sampling region with $W = 16$m surrounding the object, and the sampling level was sequentially refined from $s = 8$ to 10. The result of the lower level was inherited as the initial state for the next higher level (cf. `kamakura.mpg`).

*t.masuda@aist.go.jp

Table 1: Statistics of the experiment on Kamakura Buddha.

sampling			
s	8	9	10
$\delta = W/2^s$	6.25cm	3.125cm	1.5625cm
registration			
# iterations	4	2	3
RMS[initial]	1.16cm	4.64mm	2.64mm
RMS[final]	8.88mm	4.64mm	2.64mm
# SDF samples	287k	1175k	4780k
integrated shape model			
# triangles	182k	768k	3136k
# vertices	247k	1019k	4081k
time	0.5h	0.7h	5h
time/# iterations	7min	21min	101min

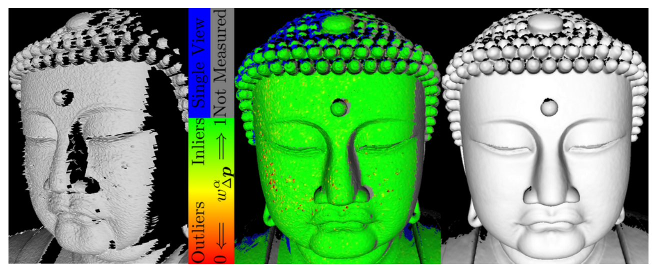

Figure 1: Measured points with large depth error appear as spikes on a data shape (left). These erroneous measurement was extracted as outliers (colored in red, middle) not to affect to generate a smooth integrated surface (right).

The final integrated shape is shown in Fig. 1, and the statistics are summarized in Tab. 1. It can be observed that the required computational resources was approximately $O(\delta^{-2})$. The erroneous measurements in the data shapes was successfully detected as outliers by comparing multiple views, and they do not appear in the final integrated model. RMS error of inliers was successfully reduced to the negligible size compared to the object size. Though no post-processing like smoothing was applied additionally, the generated surface model is very smooth. Computation time was measured on a sgi altix 350 with 4 1.4GHz-Itanium2 processors. The algorithm was parallelized but might not be completely optimized yet.

The proposed method is general, and its requirement is only that the closest point from an arbitrary point can be determined with surface orientation. We have shown that the algorithm is efficiently applicable even on a large dataset, and we look forward to apply it on more datasets in various real applications.

References

http://www.cyra.com/.

MASUDA, T. 2003. Registration and integration of multiple range images by matching signed distance fields for object shape modeling. *Computer Vision and Image Understanding 87*, 51–65.