Part 1 - General Information

<table>
<thead>
<tr>
<th>Project Title:</th>
<th>Understanding Motion: Surface 3D Deformation From Video Data</th>
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<tr>
<td>Swiss Principal Investigator(s):</td>
<td>Prof. P. Fua, EPFL, Lausanne, Switzerland</td>
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<tr>
<td>Project Start:</td>
<td>01/09/09</td>
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<tr>
<td>Project Duration:</td>
<td>36 months</td>
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<td>Indian Principal Investigator(s):</td>
<td>Prof. S. Shandran, IIT Bombay, Mumbai, India.</td>
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Part 2 - Scientific Information

A) SYNTHESIS OF THE PROJECT

3D shape recovery of deformable surfaces from single images is plagued by ambiguities. Most recent approaches have relied on combining textural clues with appropriate deformation models to overcome them. In our own work, we have shown this paradigm to be extremely effective either when the surfaces are sufficiently textured or when the models can be learned from training data. However, these approaches cannot handle poorly textured surfaces without a priori knowledge about their physical nature.

Such an ability would be required to model arbitrary objects in random videos, which is what it would take to make our algorithms applicable in a broad context. Furthermore, this is something humans can do very effectively even in very complicated cases that involve large deformations and substantial amounts of occlusions. This is therefore an issue worth investigating, first because it could shed light on how the human brain processes visual information and second because giving an automated system the ability to do this has many potential applications. They range from capturing organ deformation during endoscopic surgery to modeling the behavior of textiles when actually worn, and from measuring the deformation of metal sheets during crash tests to measuring those of airplane wings in flight.

B) RESULTS

A number of techniques have recently been proposed to recover the shape of a deformable 3D surface from a single image when point correspondences can be established with a reference image in which
the shape is known.\textsuperscript{1,2,3} Although these algorithms tolerate some mismatches, they will fail if there are too many of them, as happens in the presence of repetitive patterns or when the texture quality is too poor to guarantee reliable correspondences.

To overcome this difficulty, we have developed an algorithm that simultaneously solves for 2D correspondences and 3D shape by optimizing a single objective function over both the set of all possible correspondences and the set of all possible shapes. This amounts to solving a mixed integer quadratic problem, which is NP-hard in general. We therefore developed a branch-and-bound solver and showed that, in practice, it yields excellent approximate solutions. In challenging situations, our approach outperforms reconstruction methods relying on correspondences pre-computed by matching appearance descriptors.\textsuperscript{4}

This approach, however, still assumes that correspondences can be established, which is not necessarily true if the surface is largely featureless. We have proposed a novel approach that exploits shading information for surface reconstruction. The method can operate under complex lighting and handle surfaces that are sparsely textured. At the heart of our algorithm is a set of mappings from intensity patterns to 3D local surface shapes, which are learned using machine-learning techniques. We also proposed a principled approach to piecing together the resulting local shape estimates to a single continuous and well-formed surface. We demonstrated the effectiveness of our approach on challenging synthetic and real images, and show that it outperforms state-of-the-art texture-based shape recovery and shape-from-shading techniques. To the best of our knowledge, ours is the first method for deformable surface reconstruction, which can generalize to complex lighting environment.\textsuperscript{5}

Finally, we have explored new ways to handle occlusions, which are troublesome for almost all computer vision algorithms. In the case of deformable surfaces, we should expect parts of the surface, and sometimes the whole of it, to be occluded either by itself or by some other object. Our key intuition was that portions of the surface that are visible in some frame can be reliably reconstructed in that frame; further, the reliable portions can be stitched together to find even missing portions, much the way a human eye would hallucinate. Our technique is based on optimization in Riemannian shape spaces, and we demonstrated its efficacy on non-elastic surfaces without requiring any kind of machine learning methods.\textsuperscript{6}

\section*{C) List of Publications}

\textsuperscript{1} M. Perriollat, R. Hartley, and A. Bartoli. Monocular template-based reconstruction of inextensible surfaces. In BMVC, 2008.
\textsuperscript{3} M. Salzmann and P. Fua. Linear local models for monocular reconstruction of deformable surfaces Pattern Analysis and Machine Intelligence, IEEE Transactions on 33 (5), 931-944, 2011.
\textsuperscript{4} A. Shaji, A. Varol, L. Torresani and P. Fua, Simultaneous Point Matching and 3D Deformable Surface Reconstruction, Conference on Computer Vision and Pattern Recognition, San Francisco, CA, June 2010.
\textsuperscript{5} A. Varol, A. Shaji, M. Salzmann and P. Fua, Monocular 3D Reconstruction of Locally Textured Surfaces, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 34, Nr. 6, June 2012.
\textsuperscript{6} Shaji, A. Varol, P. Fua, Yashoteja, A. Jain and S. Chandran, Resolving Occlusion in Multiframe Reconstruction of Deformable Surfaces, CVPR Workshop on Non-Rigid Shape Analysis and Deformable Image Alignment, 2011.
Publications in reviewed journals

A. Varol, A. Shaji, M. Salzmann and P. Fua, Monocular 3D Reconstruction of Locally Textured Surfaces, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 34, Nr. 6, June 2012.

Publications in reviewed conferences
