## **Volume-10| Issue-12| 2022 Research Article DEVELOPMENT OF STATIC AND DYNAMIC ALGORITHMS FOR FILTRING**

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**Introduction:** Besides image processing, filtering techniques have also been utilized for processing 3D geometry. Indeed, many geometric descriptors such as normals and vertex positions can be considered as signals defined on twodimensional manifold surfaces, where image filtering methods can be naturally extended and applied. For example, the bilateral filter has been adapted for featurepreserving mesh smoothing and denoising. Development of new geometry filters has also been inspired by other techniques that improve upon the original bilateral filter. Among them, the joint bilateral filter determines the filtering weights using the information from a guidance image instead of the input image, and achieves more robust filtering results when the guidance provides reliable structural information. One limitation of this approach is that the guidance image has to be specified beforehand, and remains static during the filtering processing. For image texture filtering, Cho et al. Address this issue by computing the guidance using a patch-based approach that reliably captures the image structure. This idea was later adopted by Zhang et al. For mesh denoising, where a patch-based guidance is computed for filtering the face normals. Another improvement for the joint bilateral filter is the rolling guidance filter proposed, which iteratively updates an image using the previous iterate as a dynamic guidance, and is able to separate signals at

different scales. Recently, this approach was adapted by Wang et al. To derive a rolling guidance normal filter (RGNF), with impressive results for scale-aware geometric processing. For guided filtering, the use of static vs dynamic guidance presents a trade-off between their properties. Static guidance enables direct and intuitive control over the filtering process, but is not trivial to construct a priori for general shapes. Dynamic guidance, such as the one used in RGNF, is automatically updated according to the current signal values, but can be less robust when there are outliers or noises in the input signal. Recently, Ham et al. Combine static and dynamic guidance for robust image filtering. Inspired by their work, we propose in this paper a new approach for filtering signals defined on mesh surfaces, by utilizing both static and dynamic guidances. The filtered signal is computed by minimizing a target function that enforces consistency of signal values within each neighborhood, while incorporating structural information provided by a static guidance. To solve the resulting noncovex optimization problem, we develop an efficient fixed-point iteration solver, which significantly outperforms the majorization-minimization (MM) algorithm proposed for similar problems. Moreover, unlike the MM algorithm, our solver can handle constraints such as unit length for face normals, which are important for geometry processing problems. Our solver iteratively updates the signal values by combining the original signal with the current signal from a spatial neighborhood. The combination weights are determined according to the static input guidance as well as a dynamic guidance derived from the current signal. The proposed method, called static/dynamic (SD) filtering, benefits from both types of guidance and produces scale-aware and feature-preserving results.



**Materials:** The proposed method can be applied to different signals on mesh surfaces. When applied to face normals followed by vertex updates, it filters geometric features according to their scales. When applied to mesh colors obtained from texture mapping, it filters the colors based on the metric on the mesh surface. In addition, utilizing the scale-awareness of the filter, we apply it repeatedly to separate signal components of different scales; the results can be combined according to user-specified weights, allowing for intuitive feature manipulation

and enhancement. Extensive experimental results demonstrate the efficiency and effectiveness of our filter. We also release the source codes to ensure reproducibility

**Methods**: We propose a new method for vertex update according to face normals, using a nonlinear optimization formulation that enforces the face normal conditions while preserving local triangle shapes. The vertex positions are computed by iteratively solving a linear system with a fixed sparse positive definite matrix, which is done efficiently via pre-factorization of the matrix. Compared with existing approaches, our method produces meshes that are more consistent with the filtered face normals.

**Results:** Our main contributions include:

• we extend the work of Ham et al. and propose an SD filter for signals defined on triangular meshes, formulated as an optimization problem;

• we develop an efficient fixed-point iteration solver for the SD filter, which can handle constraints such as unit normals and significantly outperforms the MM solver from;

• we propose an efficient approach for updating vertex positions according to filtered face normals, which produces new meshes that are consistent with the target normals while preserving local triangle shapes;

• based on the SD filter, we develop a method to separate and combine signal components of different scales, enabling intuitive feature manipulation for mesh geometry and texture color.

In the past, various filtering approaches have been proposed to process mesh geometry. Early work from Taubin and Desbrun et al. Applied low-pass filters on meshes, which remove high-frequency noises but also attenuate sharp features. Later, Taubin proposed a two-step approach that first performs smoothing on face normals, followed by vertex position updates using anisotropic filters. To enhance crease edges, Ohtake et al. Applied anisotropic diffusion to mesh normals before updating vertex positions. Chuang and Kazhdan developed a framework for curvatureaware mesh filtering based on the screened Poisson equation. An important class of mesh filtering techniques is based on the bilateral filter. On images, the bilateral filter updates a pixel using a weighted average of its neighboring pixels, with larger contribution from pixels that are closer in spatial or range domain. It can smooth images while preserving edges where there is large difference between neighboring pixel values. Different methods have been developed to adapt the bilateral filter to mesh geometry. Fleishman et al. Applied the bilateral filter to the mesh vertex positions for feature-preserving mesh denoising. Zheng et al. The bilateral filter to mesh face normals instead, followed by vertex position update to reconstruct the mesh shape. Solomon et al. Proposed a framework for bilateral filter that is applicable for signals on general domains including images and meshes, with a rigorous theoretical foundation. Besides

denoising, bilateral filtering has also been applied for other geometry processing applications such as point cloud normal enhancement and mesh feature recovery. The bilateral filter inspired a large amount of follow-up work on image filtering. Among them, the joint bilateral filter extends the original bilateral filter by evaluating the spatial kernel using a guidance image. It can produce more reliable results when the guidance image correctly captures the structural information of the target signal.

This property was utilized by Eisemann & Durand and Petschnigg et al. To filter flash photos, using corresponding non-flash photos as the guidance. Kopf et al. The joint bilateral filter for image upsampling and structure-preserving image decomposition, respectively. In particular, a patch-based guidance is constructed in to capture the input image structure. This idea was later adopted for filtering mesh face normals, where the guidance normals are computed using surface patches with the most consistent normals. Zhang et al. Proposed a different approach to guidance construction in their iterative rolling guidance filter, where the resulting image from an iteration is used as a dynamic guidance for the next iteration. The rolling guidance filter produces impressive results for scale-aware image processing, and is able to filter out features according to their scales. Wang et al. adapted this approach to filter mesh face normals; the resulting rolling guidance normal filter enables scale-aware processing of geometric features, but is sensitive to noises on the input model. Recently, Ham et al. Proposed a robust image filtering technique based on an optimization formulation that involves a nonconvex regularizer. Their technique is effectively an iterative filter that incorporates both static and dynamic guidances, and achieves superior results in terms of robustness, feature-preservation, and scale-awareness. Our SD filter is based on a similar optimization formulation, but takes into account the larger filtering neighborhoods that are necessary for geometry signals. It enjoys the same desirable properties as its counterpart in image processing. In addition, the numerical solver proposed in this can only handle unconstrained signals, and is less efficient for the large neighborhoods used in our formulation. We therefore propose a new solver that outperforms the one from [12], while allowing for constrained signals such as unit normals. Feature-preserving signal smoothing can also be achieved via optimization. Notable examples include image smoothing algorithms that induce sparsity of image gradients via `0- norm or `1-norm regularization. These approaches were later adapted for mesh smoothing and denoising. Although effective in many cases, their optimization formulation only regularizes the signal difference between immediately neighboring faces. In comparison, our optimization compares signals within a neighborhood with user-specified size, which provides more flexibility and achieves better preservation of large-scale features. From a signal processing point of view, meshes can be seen as a

combination of signals with multiple frequency bands, which also relates with the scale space analysi. Previous work separate geometry signals of different frequencies using eigenfunctions of the heat kernel or the Laplace operator. Although developed with sound theoretical foundations, such approaches are computationally expensive. Moreover, as specific geometric features can span across a wide range of frequencies, it is not easy to preserve or manipulate them with such approaches. The recent work from Wang et al. Provides an efficient way to separate and edit geometric features of different scales, harnessing the scaleaware property of the rolling guidance filter. Our SD filter also supports scaleaware processing of geometry signals, with more robustness than RGNF thanks to the incorporation of both static and dynamic guidances.

**Conclusion:** We present the SD filter for triangular meshes, which is formulated as an optimization problem with a target energy that combines a quadratic fidelity term and a nonconvex robust regularizer. We develop an efficient fixed-point iteration solver for the problem, enabling the filter to be applied for interactive applications. Our SD filter generalizes the joint bilateral filter, combining the static guidance with a dynamic guidance that is derived from the current signal values. Thanks to the joint static/dynamic guidance, the SD filter is robust, feature-preserving and scale-aware, producing stateof-the-art results for various geometry processing problems. Although our solver can incorporate simple constraints such as unit length for normal vectors, we do not consider

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