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Morphorider:
Acquisition and Reconstruction of 3D Curves with Mobile Sensors

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Abstract—This paper introduces a new method for real-time shape sensing. Using a single inertial measurement unit (IMU), our method enables to scan physical objects and to reconstruct digital 3D models. By moving the IMU along the surface, a network of local orientation data is acquired together with traveled distances and network topology. We then reconstruct a consistent network of curves and fit these curves by a globally smooth surface. To demonstrate the feasibility of our approach, we have constructed a mobile device called the Morphorider, which is equipped with a 3AXM-sensor node and an odometer for distance tracking.

Index Terms—Shape measurement, sensor systems, reconstruction algorithms.

I. INTRODUCTION & RELATED WORK

The use of inertial micro sensors is common in many domains. Traditionally, they are at the heart of navigation systems to maneuver aircrafts, satellites or unmanned vehicles. Only recently, the use of inertial sensors for curve and surface reconstruction has emerged. The novelty of this reconstruction problem is to deal purely with orientation and distance data instead of point clouds traditionally acquired using optical 3D scanners. While a few pioneering methods were proposed in the last decade, shape sensing still remains a challenging task due to the inherent issues: inertial sensors only provide local orientations but no spatial locations; moreover, raw data from inertial sensors is inconsistent and noisy.

Previous works on shape from sensors proposed devices with a fixed connectivity and known distances between sensor nodes: the sensors were organized uniformly on a 1D ribbon [1] or on a regular 2D grid [2,3]. Multiple ribbons were employed to acquire networks of curves on a surface, using a comb structure [4] or patches with boundary from geodesic curves [5]. However, these ribbons cannot be placed on the surface arbitrarily as they will inevitably follow geodesic curves. Grids of sensor nodes are limited to specific types of surfaces (e.g., developable surfaces isometric to planar sheets). While most existing methods work in real-time, they adopt various heuristics to glue the acquired curves together in order to have a closed network with proper topology of ribbons or a grid.

This paper considers a different setup: a device with a single IMU is moved along a virtual network of curves on the scanned surface, and the data is acquired interactively. The advantages are multiple. \textit{a)} The topology of the curve network is no longer fixed by the device. Consequently, this allows us to acquire a much broader family of shapes than with previous methods. \textit{b)} The size of the object is no longer limited by the size of a pre-designed grid. \textit{c)} A very dense set of orientation data is available, which significantly improves the precision of our method.

Our contribution is twofold. First, we introduce the Morphorider, a prototype of a sensor-instrumented device for dynamic acquisition of orientations and distances along surface curves. Second, we demonstrate how the inherent noise and inconsistency of the data captured by the sensor device can be handled to produce a network of smooth curves on the scanned surface. Our main insight is to perform the filtering in the space of orientations and only integrate afterwards to get the positions. We apply the framework introduced in [6] in order to integrate the orientation data. Note that the proposed framework is not limited to the dynamic setup, and can also be used in combination with fixed-topology devices without modification. Possible applications are countless and include smart materials [5], shape digitization [6], medical scanning [3] and Structural Health Monitoring (SHM) [2].

II. ACQUISITION DEVICE

In this section we describe the Morphorider, a novel MEMS-based dynamic device, which is used for data acquisition. The key idea is to provide a device which can trace an unconstrained virtual network of curves on the scanned surface. This enables acquisition and reconstruction of a broader family of shapes than existing fixed-topology devices.

\textit{a)} Sensors of orientation: To measure the orientation of the device, we use inertial sensors able to provide their rotation with respect to a measured field. Concretely, we use: a 3-axis accelerometer providing the angle with respect to the Earth’s...
gravity field when static (the vertical direction); and a 3-axis
magnetometer providing the angle with respect to the Earth’s
magnetic field, as long as there are no magnetic perturbations.
An orthonormal frame that represents the 3D orientation is
determined by combining the information from both sensors.
The sensors are placed in the device so that one of the axes
of the orthonormal frame is aligned with the motion axis.
The orientations are estimated from sensor measurements by
solving the Wahba’s problem using SVD [7,8].

b) Sensor of displacement: Orientations are by them-
selves not sufficient to reconstruct the spatial locations, we
also need to know the displacement of the device along the
scanned curves. To this end, we use an odometer: the encoder
disk sends a tick when 1/500 of a round is traveled. The
displacement of the Morphorider has to be controlled to avoid
slidings.

c) Data collection: The sensor data are read via a serial
bus connected to a microcontroller managed by a software
driver allowing to communicate with the device. Values from
bus connected to a microcontroller managed by a software
driver allowing to communicate with the device. Values from

The Morphorider provides orientations and distances along
a network of smooth curves on a surface. We will now use
these data to reconstruct the network: this network is then
interpolated with existing surface methods.

a) Problem formulation: We consider a collection \( \Gamma \) of
\( G^3 \) smooth curves embedded on a 2-manifold surface \( S \subset \mathbb{R}^3 \).
Denote by \( \mathbf{x} : [0, L] \rightarrow \mathbb{R}^3 \) the natural parametrization
of \( \gamma \in \Gamma \) where \( L \) is the length of \( \gamma \). For a fixed point \( \mathbf{x} \) on
the curve, the orthonormal Darboux frame \( \mathcal{D} = (\mathbf{T}, \mathbf{B}, \mathbf{N}) \)
consists of the unit tangent vector \( \mathbf{T} = \dot{x} \), the outward surface
normal \( \mathbf{N} \), and the binnormal \( \mathbf{B} = \mathbf{N} \times \mathbf{T} \) [9]. We represent
the Darboux frame \( \mathcal{D} \) as an orientation matrix \( \mathbf{A} = [\mathbf{T} \mathbf{B} \mathbf{N}] \)
which is a member of the special orthogonal group \( \text{SO}(3) \).

Knowing the topology of network and a set of orientations
\( \mathbf{A}_i = \mathbf{A}(x(d_i)) \) sampled at known distances \( d_i \in [0, L] \)
for each curve \( \gamma \), the goal is to retrieve the unknown positions \( \mathbf{x} \).

b) Pre-filtering: The noisy raw data are first pre-
processed to obtain a smooth sampling with respect to arc
length. In this step, we use unit quaternions to represent
the orientations; see [7] for details and conversion relations.
First, we remove the outliers and the duplicate measures; we
then fix the sampling distance \( h_{\text{fix}} \) and compute uniform

\[ \mathbf{q}_k = \text{mean}_{\mathbf{q}_i \in \mathcal{E}_k} \mathbf{q}_i, \quad \mathcal{E}_k, \mathcal{W}_k = \exp \left[ -\frac{1}{2} \left( \frac{\mathbf{q}_k - \sigma \mathbf{h}_k}{\sigma \mathbf{h}_k} \right)^2 \right]. \]

The parameter \( \sigma \in [0.2, 0.5] \) controls the radius of convol-
ung. Means are computed using the \( q \) method [7].

c) Filtering by regression on \( \text{SO}(3) \): The next step is to
smooth the orientations and ensure the consistency of surface
normals at intersections of curves. To this end we use a variant
of smoothing splines on the manifold \( \text{SO}(3) \). Recall that a
smoothing spline \( \mathbf{x} : [t_0, t_N] \rightarrow \mathbb{R}^n \) for a set of points \( \mathbf{p}_i \in \mathbb{R}^n \)
iminizes the energy

\[ \sum_{i=0}^{N} \| \mathbf{x}(t_i) - \mathbf{p}_i \|^2 + \int_{t_0}^{t_N} \lambda \| \dot{x} \|^2 + \mu \| \ddot{x} \|^2 dt. \] \( (1) \)

The weights \( \lambda, \mu > 0 \) control stretching and bending of the
spine, respectively. We will write this energy as \( E = E_0 + \lambda E_1 + \mu E_2 \). Similarly, smoothing splines have been defined for
data on Riemannian manifolds [10]. To smooth the orientation
data \( \mathbf{A}_i \) on the manifold \( \text{SO}(3) \), we use the following energies
(see [11] for details):

\[ E_0(\gamma) = \frac{1}{h} \sum_{i=0}^{N-1} \| \mathbf{A}_i - \mathbf{A}_{i+1} \|^2, \quad E_1(\gamma) = \frac{1}{h} \sum_{i=0}^{N-1} \| \dot{\mathbf{A}}_i \|^2, \quad E_2(\gamma) = \frac{1}{h^2} \sum_{i=1}^{N-1} \| \ddot{\mathbf{A}}_i \|^2. \] \( (2) \)

In our setup, the raw data \( \mathbf{A}_i \) is associated to a network
\( \Gamma \) and the above energy terms are summed over all curves
\( \gamma \in \Gamma \). Simultaneously with regression on \( \text{SO}(3) \), we solve
the consistency constraints as follows. Let \( \mathbf{X}_i, \mathbf{X}_j \) be the local
Darboux frames of two curves at their intersection. Then
the two frames are called consistent if \( \mathbf{X}_i \) is obtained by
rotating \( \mathbf{X}_j \) around the surface normal. Denote by \( \mathcal{N} \) the set
of all such pairs \( (\mathbf{X}_i, \mathbf{X}_j) \). To enforce consistency, we add a
term penalizing the difference in projection on the normal
component

\[ E_N(\Gamma) = \sum_{(\mathbf{X}_i, \mathbf{X}_j) \in \mathcal{N}} \left\| \mathbf{X}_i N - \mathbf{X}_j N \right\|^2. \] \( (3) \)

The final energy is minimized using Riemannian trust region
algorithm [12].

d) Integration: The positions \( \mathbf{x} \) are computed by solving
Poisson’s equation \( \Delta \mathbf{X} = \nabla \cdot \mathbf{T} \) where \( \mathbf{T} \) is the tangent
field extracted from the filtered orientations \( \mathbf{X} \). The differen-
tial operators are discretized via finite differences: \( \Delta \mathbf{X}_i = \frac{1}{h^2} \left( \mathbf{X}_{i-1} - 2 \mathbf{X}_i + \mathbf{X}_{i+1} \right), \quad \nabla \mathbf{T}_i = \frac{1}{h} (\mathbf{T}_i - \mathbf{T}_{i-1}). \) The above
discretization is valid for all interior vertices. At endpoints
of open curves, we directly impose the boundary conditions
\( \frac{1}{h} (\mathbf{X}_1 - \mathbf{X}_0) = \mathbf{T}_0, \quad \frac{1}{h} (\mathbf{X}_N - \mathbf{X}_{N-1}) = \mathbf{T}_N. \) The resulting
linear system \( \mathbf{LX} = \mathbf{T} \) is sparse with at most three non-zero
coefficients per row.
e) Surfacing: The reconstructed curve network is surfaced using one of the existing methods that take into account the available surface normals along the curves [6].

IV. EVALUATION & CONCLUSIONS

To enable a thorough evaluation and comparison with respect to known data, we used the Morphorider to acquire curves on two physical objects fabricated from digital models (Fig. 2): the LILIM \((1.00\text{m}\times1.00\text{m}\times0.25\text{m})\) and the CONE \((1.00\text{m}\times1.00\text{m}\times2.00\text{m})\). We then computed reconstruction error for the acquired networks: for each point \(x\) in the reconstructed network, the error is defined as the distance between \(x\) and its closest point \(x_S\) on the ground truth surface. The results for decreasing edge length \(h\) are shown in Fig. 3 and in Table I. The choice of \(h\) for concrete applications depends on the required precision or computation time (Table I).

The presented Morphorider is an innovative device providing a new way to scan physical shapes. By its displacement on the surface, our approach provides a robust curve network ready for surfacing (Fig. 2). Limitations of our method are device-related: size of the device may prevent acquisition of high-curvature regions and small details. The next generation prototype is in development.

REFERENCES


