

<https://doi.org/10.1038/s44182-026-00115-x>

Marker Information Efficacy: guiding marker design through deformation information encoding in vision-based tactile sensing



Tonghui Tang & Thrishantha Nanayakkara

Tactile perception is fundamental to manipulation and sensing, yet marker design in vision-based tactile sensors (VTS) remains largely unexplored. Conventional approaches assume that marker displacement alone suffices to characterise soft tissue deformation, without optimising marker geometry or spatial distribution. We introduce a systematic and design-centric framework based on Marker Information Efficacy (MIE) that formalises how marker properties govern the encoding of deformation information. Starting from generic marker matrices, we systematically examine how marker geometry and spatial distribution affect deformation encoding, force prediction, and computational efficiency. This analysis reveals that marker performance depends on how effectively marker design captures the dominant structure of the deformation field, thereby enabling the principled design of deformation-aligned markers for different sensing scenarios. As a representative case, the derived deformation-aligned marker demonstrates that MIE-guided marker design enables accurate force prediction using simpler predictive models with reduced computational cost. These findings establish MIE as a general and extensible design framework for VTS, effectively transforming optical markers from passive tracking tools into deformation-information-encoding components, and enabling efficient, real-time tactile sensing in contact-rich robotic manipulation.

Tactile perception is fundamental to dexterous robotic manipulation^{1–8}. Conventional tactile sensors, such as pressure, strain, capacitive, piezo-resistive, and piezoelectric transducers^{9–11} are inherently limited to discrete force measurements, making it difficult to capture continuous contact geometry^{12–14}.

To address these limitations, vision-based tactile sensors (VTS) have emerged as a class of approaches that provide a continuous representation of contact interactions, enabling detailed surface characterisation that traditional methods cannot achieve^{15–19}. Building on this capability, VTS infer external forces from visual observations of contact, transforming visual data into tactile information²⁰.

VTS can be broadly categorised into marker-based methods, which track the transformation of embedded visual features, and marker-free methods, which reconstruct contact information directly from image intensity and shading cues. Both methods offer compatibility with machine learning (ML) and have demonstrated effectiveness in vision-based tactile sensing. However, marker-free methods rely on indirect photometric cues,

such as intensity and shading, to infer contact information, which can introduce additional ambiguity, sensitivity to imaging conditions, and increased computational demands due to dense reconstruction^{21–23}. In contrast, marker-based approaches provide explicit, robust, and directly observable representations of deformation through visual features, thereby enabling more stable and tractable inference of underlying forces and making them more widely adopted for force estimation tasks^{24–26}.

Despite these advances, existing marker-based VTS still face fundamental limitations, as they lack a principled mechanism for encoding deformation information at the representation level^{27–29}.

Current approaches predominantly treat markers as passive tracking tools, representing deformation primarily through independent marker displacements, while overlooking the role of marker design as an information-encoding mechanism. Intrinsic properties of markers, such as shape, size, density, spatial arrangement, and area change, are not systematically incorporated into deformation representation³⁰. As a result, there is no principled mechanism linking marker design to how deformation

Morph Lab, Dyson School of Design Engineering, Imperial College London, London, UK. ✉ e-mail: tonghui.tang22@imperial.ac.uk; t.nanayakkara@imperial.ac.uk

Table 1 | Comparison of representative vision-based tactile sensing approaches with emphasis on marker representation and marker design methodology

Sensor	Transduction	Marker Features	Processing	Output	Marker Design
GelSlim ³⁰	Camera + PS + Markers	Displacement	Numeric	Force	Not investigated
F-TOUCH ¹¹	Camera + PS + Markers	Disp. + Area	Numeric	Shape + Force	Not investigated
L ³ F-TOUCH ⁴⁵	Camera + PS + Markers	Displacement	Numeric	Shape + Force	Not investigated
DIGIT ⁷	Camera + PS + Markers	Displacement	ResNet	Shape	Not investigated
GelSight ⁴	Camera + PS + Markers	Displacement	CNN	Shape + Force	Not investigated
This work (Distributed)	Camera + PS + Markers	Disp. + Area + Shape	CNN	Shape + Force	MIE-guided
This work (Concentric-Ring)	Camera + PS + Markers	Hu + Area + Shape	LR / SVR	Shape + Force	MIE-guided

Disp. denotes marker displacement, Area denotes marker area variation, Shape denotes marker shape descriptors, and Hu denotes Hu moments (see Methods, “Quantitative evaluation of deformation stability in concentric ring structures using Hu moments”). “Marker Design” indicates whether marker geometry and spatial distribution are explicitly investigated as design variables. Existing approaches employ predefined marker configurations, whereas this work systematically investigates different marker designs using the proposed Marker Information Efficacy (MIE) framework. Supplementary Note S0 provides additional discussion on the interpretation of force estimation performance reported in representative vision-based tactile sensing studies and the limitations of cross-study comparisons.

PS Photometric stereo, CNN Convolutional Neural Network, ResNet Residual Network, LR Linear Regression, SVR Support Vector Regression.

information is encoded and observed. This omission limits the establishment of a principled relationship between marker design and the fidelity of deformation representation, defined as how accurately and completely marker observations reflect the underlying elastomer deformation field. Moreover, machine learning models built on such conventional designs often rely on extracting a large number of features and employing complex learning models to compensate for the lack of geometrical alignment with deformation modes, thereby increasing computational complexity and reducing interpretability^{31–34}. This reveals a fundamental limitation of existing marker-based VTS: deformation information is not explicitly encoded at the representation level, but instead implicitly compensated by model complexity.

This limitation becomes particularly critical when deformation observations are used for force estimation. The accuracy of force estimation fundamentally depends on the quality of the input data, which, in vision-based tactile sensing, is determined by visual observations of elastomer deformation. These observations are indirect, as markers serve as proxies for the underlying deformation field. Consequently, force estimation is intrinsically governed by the fidelity of deformation representation. This establishes marker design as a fundamental determinant of sensing performance.

In force estimation, this limitation manifests differently across interaction regimes, where different force components induce distinct deformation patterns in the sensor^{3,4}. Shear force estimation is inherently coupled to normal preload and contact state, as tangential forces arise from frictional interactions that depend on the applied normal force and stick-slip conditions at the contact interface^{18,27,35}. While shear-induced marker displacements are often approximated as near-linear under controlled conditions, this behaviour reflects a conditional interaction regime rather than a general property.

In contrast, normal force estimation remains more challenging from a deformation-encoding perspective, as normal loading induces complex, spatially heterogeneous deformation of the elastomeric layer³⁶. Such heterogeneity cannot be fully captured by displacement-only representations, since out-of-plane compression and local volumetric changes play a dominant role. These effects disrupt uniform marker motion, leading to non-uniform displacement patterns and increased variability in feature extraction, which limits generalizability in force regression^{3,24,37}.

This exposes a fundamental gap: existing marker designs and feature representations are not aligned with the dominant deformation modes of the elastomer, resulting in inefficient and incomplete deformation information encoding. Normal-force-dominated interactions represent the regime in which marker design most critically determines sensing performance, highlighting the need for a principled marker design framework.

To address these challenges, we introduce Marker Information Efficacy (MIE), which defines the effectiveness of a marker design in encoding mechanically meaningful deformation information into visually observable features for tactile perception. Building upon this concept, we develop a design-centric framework that formulates marker design as a deformation-information encoding problem. Within this framework, markers are no longer treated as passive tracking tools, but as components that encode deformation information through their geometry (shape, size) and spatial distribution (density and fill factor). This concept is based on the hypothesis that deformation fields in soft tissues are inherently smooth and low-dimensional, thereby favouring marker designs that align with the dominant deformation patterns.

Deformation information is not only captured through marker displacement, but also through complementary descriptors such as area change, which reflects local compression and strain. As area change is intrinsically governed by marker properties such as shape and size, marker geometry directly determines how deformation information is generated and observed.

Starting from conventional marker matrices, markers can therefore be interpreted as discrete sampling nodes of the underlying deformation field. By analysing deformation patterns from these observations, dominant deformation modes can be identified, enabling marker geometries to be redesigned to align with these modes for different sensing scenarios. As a representative case for normal-force-dominated deformation, concentric-ring markers are derived, which capture the dominant radial deformation structure and enable accurate force prediction with reduced model complexity and computational cost^{3,38}.

Table 1 summarizes representative vision-based tactile sensing approaches, highlighting differences in sensing principles, marker representations, data processing pipelines, and tactile outputs. Although these approaches employ diverse sensing paradigms, marker design is generally treated as an implementation detail rather than a principled design variable, and its influence on deformation-information encoding has rarely been investigated systematically. These observations reveal the need for a systematic and principled investigation of marker design in vision-based tactile sensing.

To our knowledge, this study presents the first systematic investigation of marker design in vision-based tactile sensing, establishing a foundation for design-centric marker research. We present a systematic analysis of marker geometry (shape and size) and spatial distribution (density and fill factor), showing that these properties govern how deformation information is encoded into observable features, which in turn determines force-prediction accuracy. These findings establish MIE as a design-centric framework for VTS, highlighting the critical role of marker configuration and shifting markers from passive tracking tools to deformation-information-encoding components. Starting from conventional marker matrices, marker

Marker Information Efficacy (MIE) Framework

A design-centric framework for encoding elastomer deformation into visual information

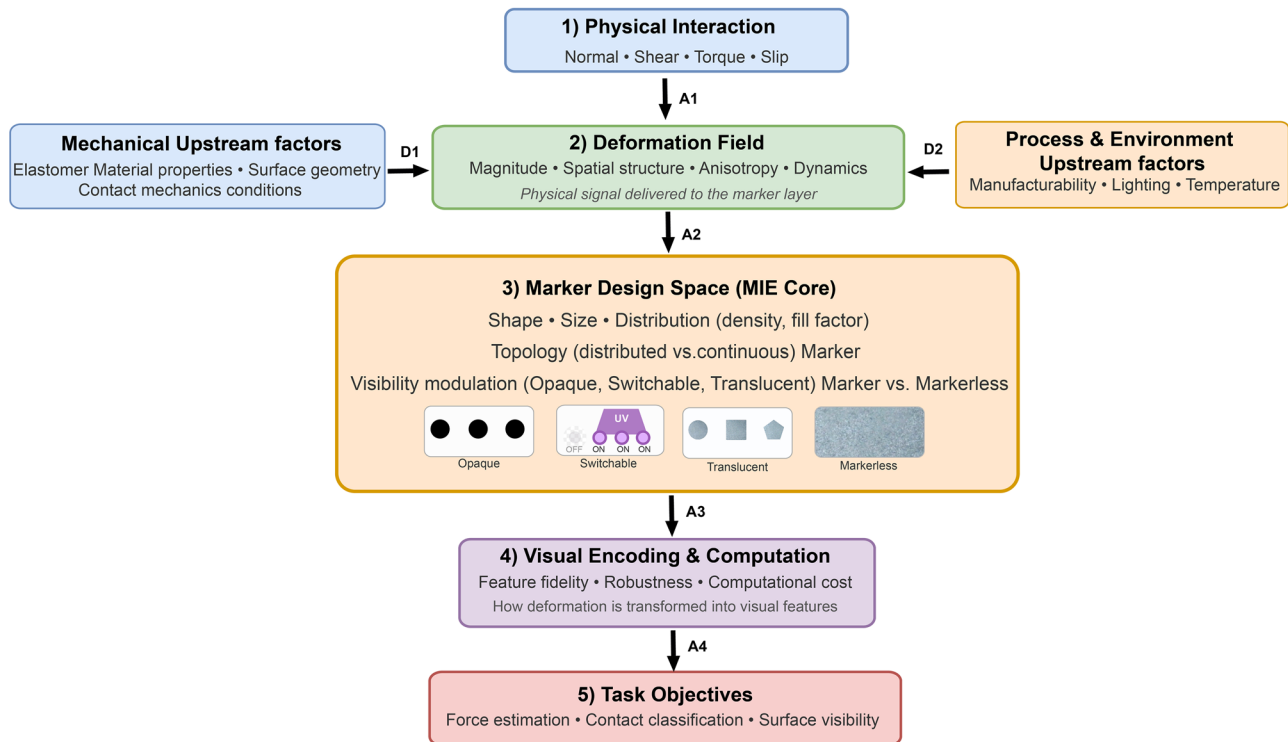


Fig. 1 | Marker Information Efficacy (MIE) framework for vision-based tactile sensing. The MIE framework organises vision-based tactile sensing into domain-defining factors (D) and abstraction stages (A), explicitly separating upstream physical and practical conditions from marker-level information encoding. In the

Physical Interaction, shear refers to tangential deformation without macroscopic relative motion, whereas slip denotes the onset of relative motion after the frictional limit is exceeded.

configurations can be systematically redesigned to align with dominant deformation modes according to specific sensing requirements, enabling improved force estimation with reduced model complexity. This framework provides a principled basis for adapting marker design across different sensing conditions. As a representative case of deformation-aligned marker design, concentric-ring markers are derived, capturing the dominant radial deformation structure and enabling accurate force prediction with reduced model complexity and computational cost. By clarifying how marker design governs deformation encoding and enabling efficient and accurate force estimation, this work establishes MIE as a general and extensible framework for marker design in vision-based tactile sensing (Fig. 1). It may be applied to contact-rich manipulation tasks such as grasp-force regulation, slip-onset detection, and in-hand regrasping.

The main contributions of this paper are summarised as follows:

- We propose a rare representation-driven perspective on visuotactile sensing in a field where data-driven methods dominate, highlighting marker design as an underexplored yet critical source of tactile information.
- We introduce the Marker Information Efficacy (MIE) framework, which formulates marker design as a deformation-information encoding problem and reinterprets optical markers as deformation information encoding components rather than passive tracking tools.
- We present a systematic and quantitative analysis of marker geometry (shape and size) and spatial distribution (density and fill factor), revealing how marker configuration governs deformation encoding and the trade-off between sensing accuracy and computational efficiency.
- We introduce a new deformation-information encoding mechanism that extends beyond displacement by incorporating area change—

coupled with marker geometry—and spatial distribution, enabling a more complete representation of deformation.

- We further establish a principled marker redesign strategy, in which marker configurations are systematically adapted to align with dominant deformation modes under different sensing conditions.
- As a representative case of deformation-aligned design, we derive concentric-ring markers for normal-force-dominated deformation, demonstrating high force estimation accuracy while simultaneously reducing model complexity and computational cost.
- We clarify the domain-dependent behaviour of marker design under normal and shear loading and establish practical design guidelines for navigating the marker design space in future visuotactile sensor development.

Results

General design and working principle

The vision-based tactile sensor used in this paper consists of two primary components: a replaceable elastomeric sensing unit and a fixed sensor body that houses the imaging and structural support system, as shown in Fig. 2a. The replaceable elastomeric unit serves as the primary interface for force sensing, while the rigid body ensures stable illumination and imaging.

To investigate the effect of contact geometry on force estimation, five indenters with distinct geometries—circular, hexagonal, pentagonal, square, and triangular—were fabricated (Fig. 2b). These indenters enabled controlled variation of contact conditions across experiments.

The fabricated sensor prototype, depicted in Fig. 2c, is integrated into a high-precision positioning system, which ensures controlled indentation. During experiments, the applied forces were recorded using a six-axis force/torque (F/T) sensor. The complete experimental setup is shown in Fig. 2d.

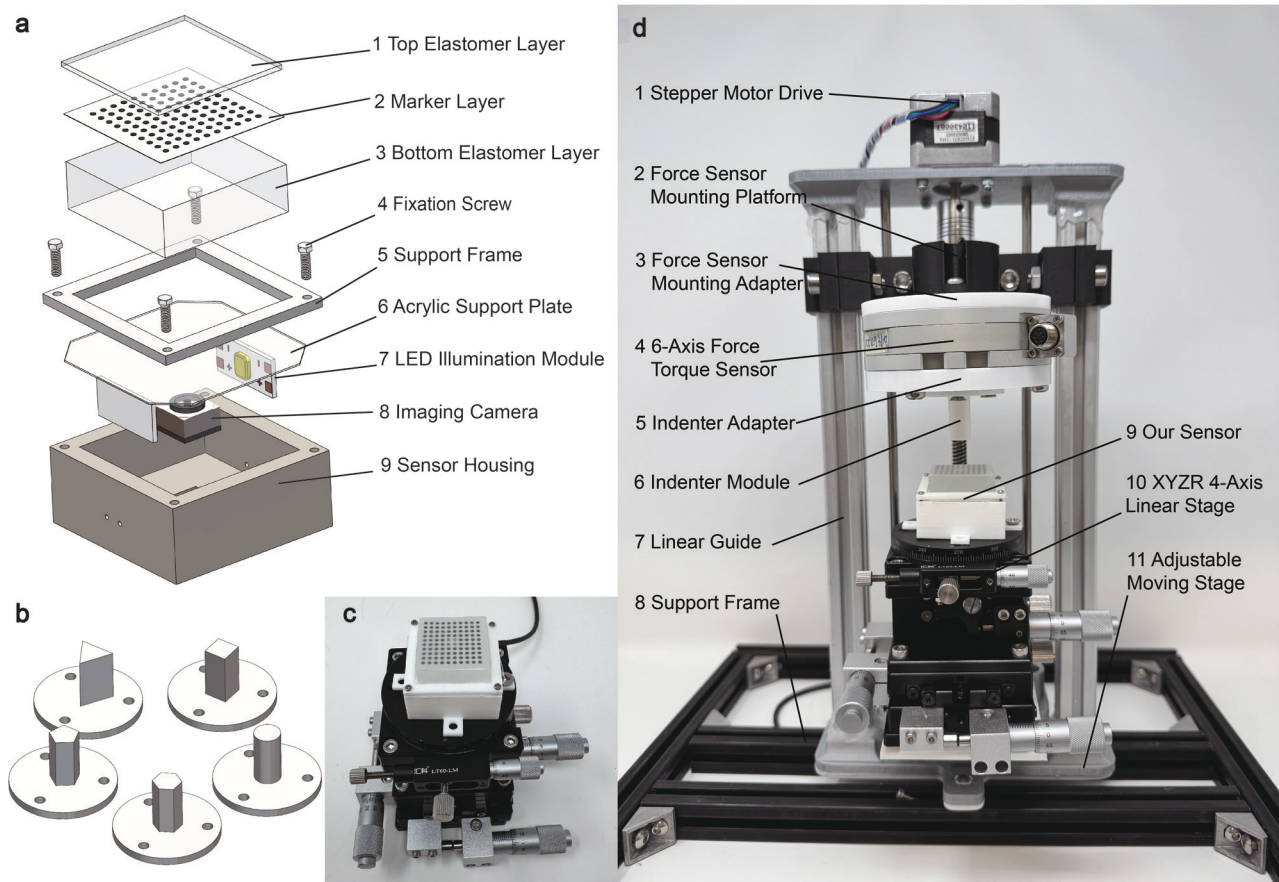


Fig. 2 | Overview of the sensor design and experimental setup. **a** Exploded view of the sensor design. **b** Indenter designs (circular, hexagonal, pentagonal, square, and triangular). **c** Physical prototype of the sensor. **d** Experimental setup.

This study investigates both distributed and concentric-ring marker configurations, as illustrated in Fig. 3. To systematically analyse the role of geometry, five shapes were implemented for distributed markers: triangle, square, pentagon, hexagon, and circle (Fig. 3(i)). Beyond these uniform layouts, we further designed distributed concentric arrangements (Fig. 3(ii), (iii)), in which markers are placed along concentric rings rather than in regular grids. This variant was motivated by the observation that deformation fields under normal loading often appear radially symmetric, and was therefore hypothesised to better capture global deformation modes while retaining the flexibility of a distributed layout. The quantitative motivation for this hypothesis is further developed in the following sections, where PCA (see Methods: Principal Component Analysis (PCA) of Marker Displacement and Area Change) demonstrates that circularly symmetric components dominate marker displacement and area change, and RSS fitting (see Methods: Concentric Ring Approximation for Deformation Quantification) verifies that concentric rings provide a compact approximation of global deformation. To test this idea more explicitly, we also introduced concentric-ring markers realised in circular, hexagonal, and pentagonal geometries (Fig. 3(iv)). Finally, to investigate the effects of marker density and fill factor, three controlled dot-array variations were introduced (Fig. 3(v); see Methods: Quantification of marker distribution): A-line (sampling point effect), B-line (contrast effect), and C-line (spatial bandwidth effect). Together, these marker configurations define the core design space of the proposed MIE framework, as shown in Fig. 1, providing a basis for analysing how marker shape, size, density, and fill factor govern deformation encoding in vision-based tactile sensing.

The displacement of distributed markers under normal loading reveals spatially heterogeneous deformation patterns that depend on marker

geometry and indenter shape. Marker displacement differs markedly across regions within the contact area, along the contact boundary, and outside the contact region, indicating that normal-force-induced deformation is inherently non-uniform and cannot be described by a simple global displacement field, in contrast to typical tangential loading scenarios. These observations highlight the importance of marker design in capturing both local compression and global material deformation within vision-based tactile sensing.

For concentric markers, deformation responses under different indenter geometries exhibit systematic differences across marker families. Circular concentric markers consistently produce radially symmetric and spatially coherent deformation patterns across all tested indenter shapes, whereas non-circular concentric markers introduce geometry-induced variations in deformation organisation due to angular features. These qualitative differences suggest that deformation-aligned marker geometry plays a critical role in shaping the visual encoding of the deformation field, motivating further analysis of how such responses translate into force estimation performance. Detailed optical-flow visualisations and deformation examples are provided in Figure S1.

Regression across marker shapes and indenters for distributed markers

To evaluate the impact of marker shape under controlled indenter conditions, we used a convolutional neural network (CNN) regression model as a baseline predictor, with marker displacements (x , y) and area changes as input features and the estimated normal force (F_z) as output. CNNs were chosen as the baseline because they are widely adopted in vision-based tactile sensing and offer robust nonlinear regression capability, providing a consistent and representative reference for comparing marker designs. This

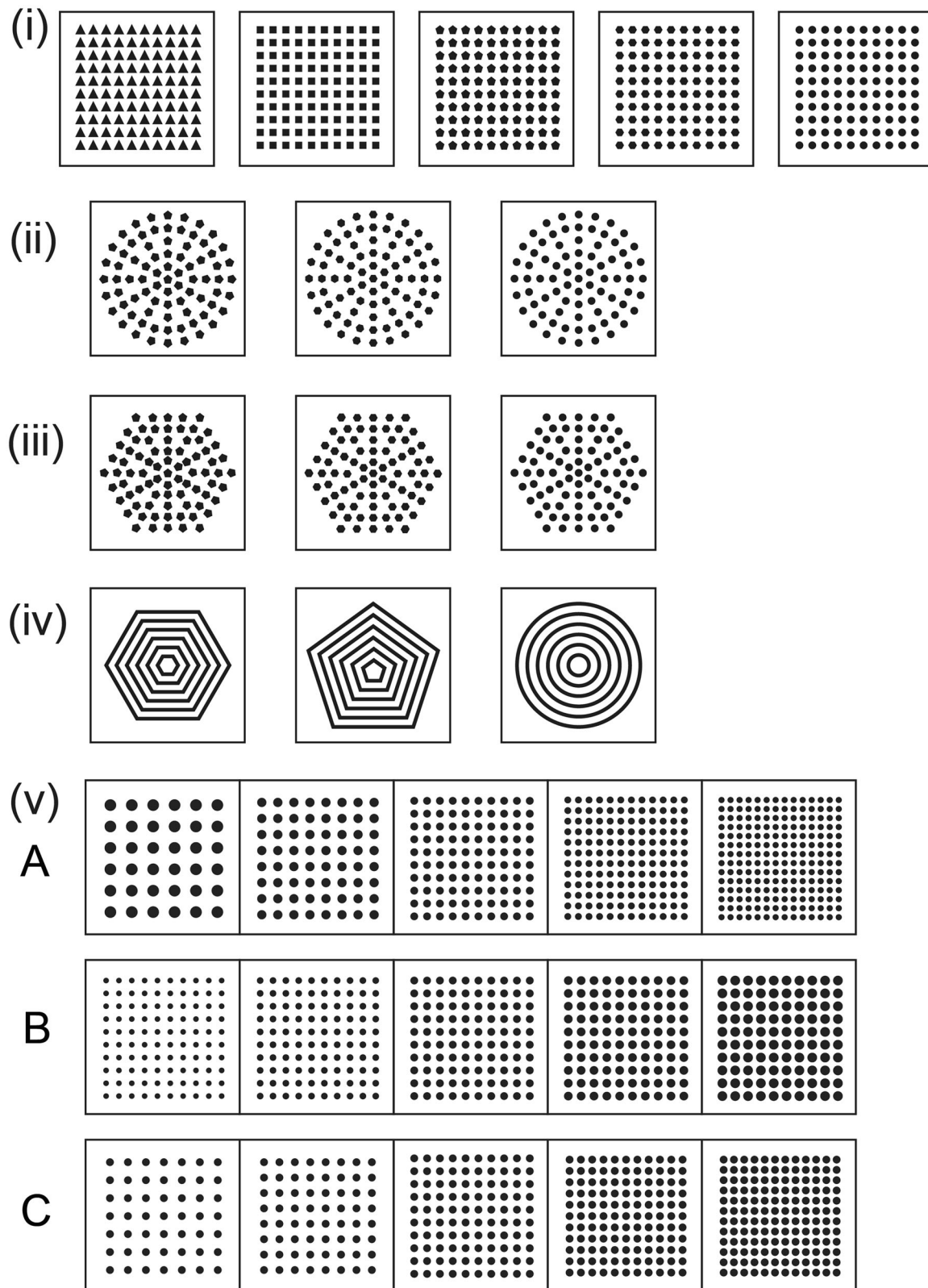
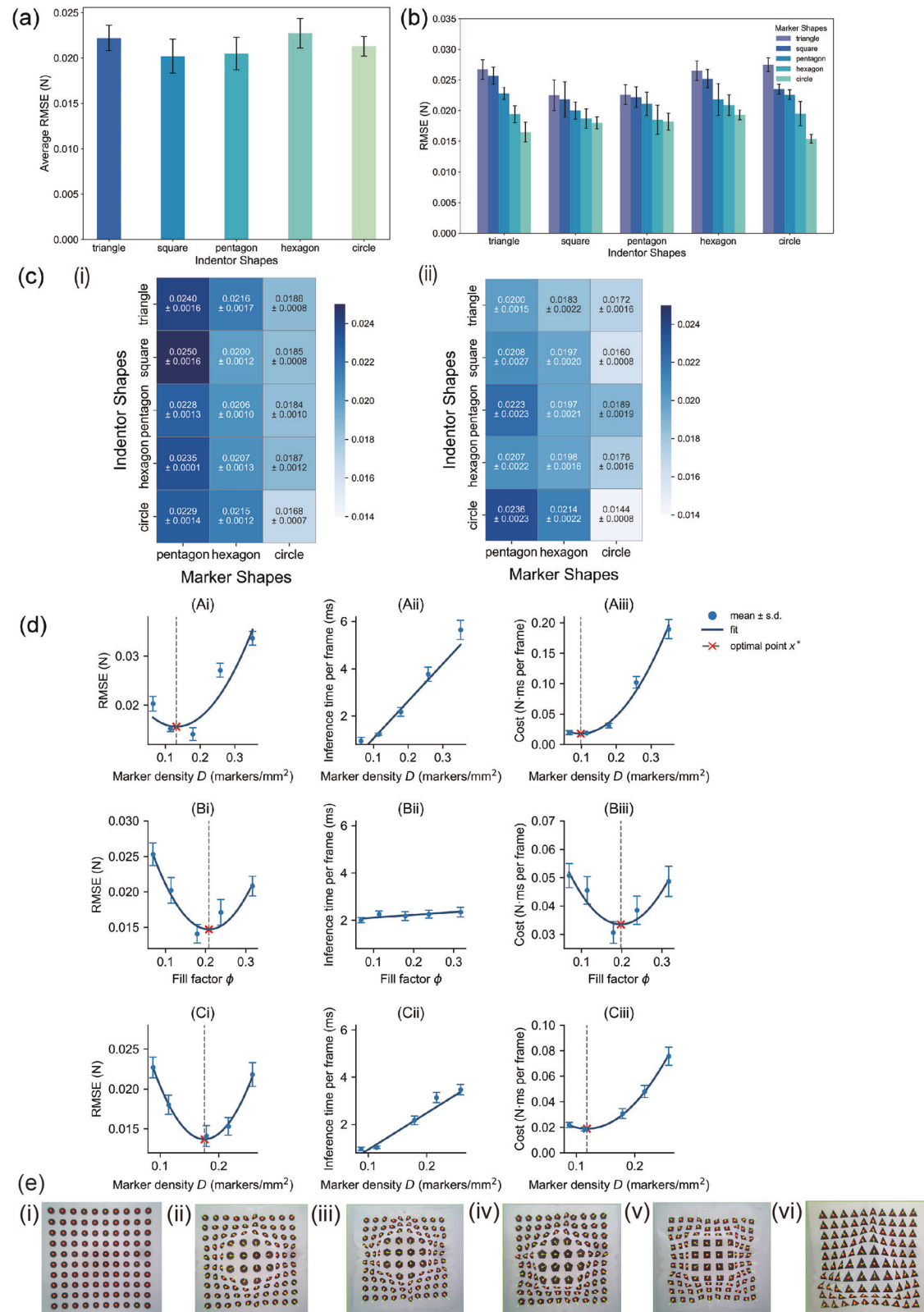


Fig. 3 | Marker Configurations. (i) distributed markers in a regular grid with five shapes (triangle, square, pentagon, hexagon, circle); (ii) distributed concentric circle arrangement; (iii) distributed concentric hexagon arrangement; (iv) concentric ring markers (hexagon, pentagon, circle); (v) three controlled variations of dot arrangements (see Methods: Quantification of marker distribution): A-line (sampling point effect), changing how many dots were placed while keeping the

proportion of the area occupied by markers similar, thereby testing the effect of sampling density; B-line (contrast effect), changing the dot size while keeping the spacing fixed, thereby altering the visual contrast of the markers; C-line (spatial bandwidth effect), changing the spacing between dots while keeping their size fixed, thereby altering how finely the deformation pattern was captured.



unified formulation ensures that performance differences reflect marker geometry rather than feature or target definitions.

Across five distributed marker geometries (circle, hexagon, pentagon, square, and triangle), the average root mean square error (RMSE) remained approximately constant across indenters (Fig. 4a), indicating that indenter shape has no significant influence on force estimation. In contrast,

substantial differences emerged between marker shapes (Fig. 4b): circular markers consistently yielded the lowest RMSE under all indenter conditions, followed by hexagonal, pentagonal, and square markers, whereas triangular markers performed worst.

Because the marker area was kept constant across all shapes, the observed differences cannot be attributed to size. Circular markers further

Fig. 4 | Evaluation of the impact of marker geometry, distribution, and density on force prediction performance. **a** Average RMSE across different indenter shapes, showing that contact geometry has limited influence on sensing accuracy. **b** Comparison of RMSE across marker shapes under different indenters, highlighting the superior performance of circular markers. **c** Heatmaps of RMSE for (i) the distributed concentric hexagon arrangement shown in Fig. 3(iii) and (ii) the distributed concentric circle arrangement shown in Fig. 3(ii). Each heatmap compares combinations of five indenter shapes and three marker shapes. **d** Trade-offs between accuracy and computational efficiency across controlled density variations. (Ai–Ci) RMSE as a function of marker density or fill factor, with quadratic fits and

optimal operating points (x^*) indicated. (Aii–Cii) Corresponding inference time per frame, showing approximately linear scaling with density but weak dependence on fill factor. (Aiii–Ciii) Combined cost function, defined as RMSE multiplied by inference time, quantifying the balance between accuracy and efficiency; quadratic fits and optimal points are indicated. Error bars represent mean $\pm$ s.d. **e** Representative real VTS images of different distributed marker shapes under deformation. **e(i)** Undeformed circular markers (baseline). **e(ii)** circular markers. **e(iii)** hexagonal markers. **e(iv)** pentagonal markers. **e(v)** square markers. **e(vi)** triangular markers.

benefit from smoother boundaries and fewer sharp corners, which improve tracking stability and reduce feature noise compared with polygonal markers. This enhanced precision in marker tracking directly supports more reliable force prediction. Beyond tracking, geometric symmetry also plays a role: circular markers promote uniform strain distribution and low-dimensional deformation features, whereas polygonal markers, particularly triangular and square ones, introduce edge-driven stress concentrations that increase nonlinearity.

To further validate that this effect is independent of spatial distribution, we compared marker shapes across grid-like and concentric-ring configurations. The heatmaps in Fig. 4c visualise the RMSE distribution across different marker layouts, where darker shades represent higher error and lighter shades indicate lower error. The influence of marker shape was consistent across both configurations: circular markers always yielded the lowest RMSE, followed by hexagonal, pentagonal, and square markers, while triangular markers consistently performed worst. These results establish marker shape, rather than indenter or spatial layout, as the primary determinant of regression accuracy. While marker geometry emerged as an important factor influencing regression accuracy, spatial distribution may further determine how effectively deformation is sampled.

Density and fill factor optimisation for distributed markers

Marker distribution governs how deformation is sampled and how reliably markers can be tracked, thereby constraining the achievable accuracy of vision-based tactile sensing while also defining a fundamental trade-off between information content, tracking robustness and computational cost. Building on the mathematical definitions introduced in the Methods: Quantification of marker distribution, we next investigated how different aspects of marker distribution influence sensing performance.

Here, marker density refers to the number of markers per unit sensing area, whereas the fill factor denotes the proportion of the surface covered by markers; together, these parameters shape the balance between information capture, visibility and efficiency. We systematically varied these factors along three orthogonal dimensions, as illustrated in Fig. 3(v): (i) the sampling resolution line (A-line), where the number of markers was increased by proportionally shrinking their diameter and spacing so that overall coverage remained approximately constant, thereby isolating the effect of sampling resolution; (ii) the contrast line (B-line), where spacing was fixed but marker diameter was varied, altering the fill factor and the visibility of individual markers; and (iii) the spatial bandwidth line (C-line), where marker size was fixed while spacing was adjusted, simultaneously modifying density and fill factor. Performance was quantified in terms of prediction accuracy, per-frame inference time, and a combined cost function as the product of RMSE and inference time, capturing the accuracy-efficiency trade-off.

The sampling resolution line (A-line, Fig. 4 d(Ai–Aiii)): Accuracy improved as density increased from sparse arrays to intermediate levels because additional markers more completely sampled the deformation field. Beyond this range, oversampling introduced redundant features and amplified tracking noise, degrading performance. Inference time rose roughly linearly with density. Consequently, the cost function exhibited a pronounced U-shape with a minimum at intermediate densities: on the left branch, it was dominated by error (high RMSE at low density), whereas on

the right branch, it was increasingly driven by computation (rising time with dense arrays).

The contrast line (B-line, Fig. 4d(Bi–Biii)): Very small markers with low fill factor yielded high error due to poor visibility and noisy feature extraction. Accuracy peaked at intermediate diameters, while oversized markers averaged out local deformations and occasionally overlapped, reducing robustness. Inference time remained nearly constant across this line; therefore, the cost function closely mirrored accuracy, attaining its minimum at the same intermediate fill factor.

The spatial bandwidth line (C-line, Fig. 4d(Ci–Ciii)): Reducing spacing initially improved accuracy by enhancing spatial resolution, but performance declined once markers became visually crowded and difficult to track. Here, inference time scaled with density (which is linearly tied to fill factor in this manipulation), so the cost function again formed a U-shape with an optimum at intermediate spacing: accuracy limits dominated the left branch, whereas computational cost dominated the right.

Taken together, the three lines consistently showed that performance does not change monotonically with density. Instead, an optimal density regime emerges, beyond which further densification yields diminishing or negative returns, reflecting a convergence phenomenon shaped by the interplay of sampling resolution, marker visibility and spatial bandwidth. By explicitly combining accuracy and efficiency, the cost function generalized these findings across conditions, demonstrating that intermediate marker configurations consistently minimize the joint penalty of error and computation. As a practical guideline, our results suggest that marker densities and fill factors in the range of approximately 10–20% provide a robust operating window for future vision-based tactile sensor designs. Beyond local density and coverage, an open question is whether global marker arrangements can more directly align with deformation symmetries, as such alignment may provide a more efficient way to capture deformation than merely increasing the number of sampling points.

Principal Component Analysis (PCA) of marker displacement and area change

Building on our observations, soft tissue deformation under normal force loading often exhibits radial symmetry. Motivated by this, we hypothesised that circularly symmetric layouts are particularly well suited to capture global deformation modes. To test this hypothesis, we analysed the deformation fields recorded by distributed markers using Principal Component Analysis (PCA). Functionally, these markers act like sampling nodes in a finite element mesh: they do not alter the deformation but provide discrete observations of how the soft tissue deforms under load. PCA extracts the dominant modes from these observations, quantifying whether deformation is governed by a few global patterns or dispersed across many local components. In this analysis, PCA was applied to feature vectors consisting of marker displacements (x, y) and area changes, allowing us to evaluate how efficiently different geometries encoded the underlying deformation field.

Table 2 summarises the explained variance ratios for different indenter geometries. In all cases, PC1 overwhelmingly dominates, accounting for more than 98% of the variance, whereas PC2 contributes marginally (1–2%) and higher-order components are consistently negligible ($< 0.1\%$). This confirms that PC1 captures the decisive deformation mode of the sensor's soft tissue layer. To obtain a representation that generalises across loading

Table 2 | Explained variance ratio (%) of the first ten principal components (PC1-PC10) for different indenter shapes

Indenter	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Circle	99.07	0.53	0.18	0.03	0.03	0.02	0.01	0.01	0.01	0.01
Hexagon	97.95	1.53	0.09	0.06	0.03	0.02	0.02	0.02	0.01	0.01
Pentagon	98.57	0.96	0.07	0.06	0.02	0.02	0.02	0.02	0.01	0.01
Square	97.60	1.84	0.08	0.06	0.03	0.03	0.02	0.02	0.02	0.02
Triangle	98.23	1.37	0.11	0.05	0.02	0.01	0.01	0.01	0.01	0.01
Average	98.28	1.25	0.11	0.05	0.03	0.02	0.02	0.02	0.01	0.01

Across all cases, PC1 overwhelmingly dominates the variance (> 97%), PC2 contributes marginally (1–2%), and higher-order components are consistently negligible (< 0.1%).

conditions, we then pooled trials across all indenter shapes for each distributed marker geometry. Figure 5a presents this pooled analysis, examining how different marker geometries encode this global mode for combined displacement and area change data.

Circular markers explained over 95% of variance with only a few principal components, whereas non-circular markers such as hexagonal, pentagonal, square, and triangular required more components. This indicated that circular markers captured deformation in a compact, low-dimensional form, while non-circular markers exhibited more dispersed and localised behaviours. This result underscores their robustness in encoding global deformation patterns and supports their use as the most efficient marker geometry for force prediction.

Pooling trials across all indenter shapes provided a general representation of soft tissue deformation. PCA on these combined data confirmed that Principal Component 1 (PC1) remained the dominant mode, accounting for the vast majority of variance across all marker geometries, consistent with the single-indenter results in Table 2. On this basis, subsequent analyses focus exclusively on PC1 as the primary descriptor of soft-tissue deformation. Since PC1 may largely reflect a radially symmetric global mode as shown in Fig. 5b(i), the next step is to test how well concentric-ring layouts approximate this deformation geometry. This analysis serves as the first step of the MIE framework, where dominant deformation modes are identified from generic marker observations, forming the basis for subsequent marker redesign.

Concentric ring approximation for deformation quantification

Figure 5 b(i) shows PC1 reveals a dominant radial symmetry in the deformation field, which directly motivated us to explore concentric ring approximations as a means to capture the deformation characteristics of our sensor's soft tissue layer more effectively. To quantitatively assess how well concentric rings approximate this global mode, we adopted the Residual Sum of Squares (RSS) as a measure of fitting error, since it directly evaluates the discrepancy between the observed PC1 distribution and its concentric-ring representation.

As shown in Fig. 5b(ii), circular concentric rings consistently achieve the lowest RSS across all configurations, confirming their superior ability to approximate the radial-symmetric deformation mode. In contrast, triangular and square markers yield the highest RSS values, reflecting irregular deformation patterns that are poorly captured by the concentric model. Hexagonal and pentagonal markers perform moderately, ranking just below circles but clearly outperforming triangles and squares. The largest reduction in RSS occurs as the number of rings increases from two to about five, after which the curve flattens and further rings provide only marginal improvement. This suggests a practical operating window of approximately five to seven rings, which captures most of the deformation-mode benefit while avoiding unnecessary geometric complexity or computational overhead. Unless extreme accuracy is required, this window offers a reasonable trade-off between performance gain and fabrication cost for concentric-ring layouts.

These results directly validate our initial hypothesis: because soft-tissue deformation under normal loading is predominantly radial, concentric ring

structures provide a natural and effective basis for representing this global mode. Circular markers, by aligning most closely with radial symmetry, yielded the most stable and accurate fits, confirming their superiority for deformation quantification. We next evaluate the practical implications of this design choice by validating sensor performance using concentric-ring markers. This analysis directly corresponds to the redesign step of the MIE framework, where marker geometry is systematically adapted to align with the identified dominant deformation mode.

Validation using concentric ring markers

In this context, concentric-ring markers should be understood as a case study derived from the MIE framework for normal-force-dominated deformation. Based on the concentric ring approximation analysis above, triangular and square configurations exhibited poor alignment with the radial-symmetric deformation captured by PC1, leading to unstable and inaccurate fits. Therefore, in the following validation, we focus on circular, hexagonal, and pentagonal concentric ring markers, which are more compatible with the dominant deformation mode of the soft tissue layer. To ensure consistency with the distributed-marker experiments, we employed the same shared CNN regression architecture; in this case, the input features were Hu-moment descriptors extracted from the deformation of concentric-ring structures, and the output target remained the normal force F_z . Hu moments, a set of seven invariant image descriptors widely used in computer vision, capture shape characteristics that remain invariant to translation, rotation, and scaling, making them suitable for representing global deformation features of concentric-ring structures.

The comparison of marker shape (Fig. 5c(ii)) shows that concentric circular rings consistently yield the lowest RMSE across all indenter conditions, outperforming hexagonal and pentagonal rings. Figure 5c(iii) further shows that concentric circular rings exhibit the lowest overall mean change in Hu-moment values, followed by concentric hexagonal and pentagonal rings, indicating that higher smoothness in ring geometry contributes to more uniform deformation and reduces variability in sensor response. The analysis of indenter shape (Fig. 5c(i)) shows no significant impact on RMSE, reinforcing that force-distribution geometry plays a lesser role in sensing accuracy compared to deformation quantification achieved by marker geometry, consistent with the trend observed previously for distributed-marker configurations.

These findings confirm that concentric circular rings most effectively encode radial deformation. Taken together with our earlier investigations of distributed marker geometry, size, density, and fill factor, they collectively embody the principles of the MIE framework. This motivates the next step of evaluating whether such deformation-aligned designs may also enhance computational efficiency and robustness.

MIE framework: computation-efficient model performance across marker configurations

To evaluate whether the deformation-aligned design of concentric-ring markers improves the computational efficiency of force estimation, we benchmarked nine commonly used regression models on identical datasets obtained from both distributed and concentric marker configurations, as

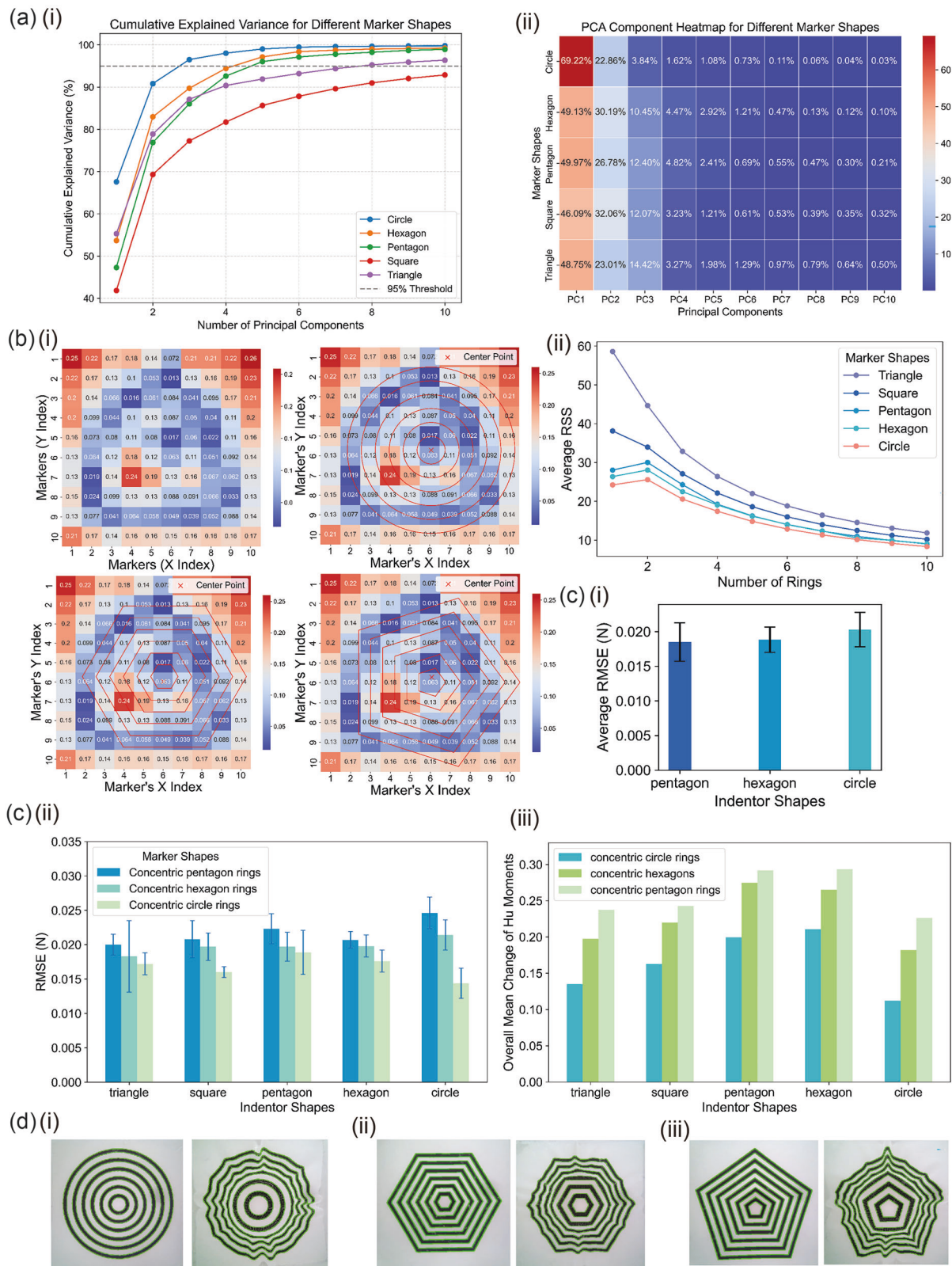


Fig. 5 | Comprehensive Analysis of Concentric Marker Shapes for Deformation Encoding and Force Prediction. **a** Principal Component Analysis (PCA) results for different distributed marker shapes. Cumulative explained variance and corresponding heatmaps of principal component contributions. **b** Contour fitting accuracy using concentric ring structures. **b**(i) Heatmaps showing PC1-based contour fitting with circular, hexagonal, and pentagonal ring fitting methods, applied across different marker distributions. **b**(ii) Average residual sum of squares (RSS) for different numbers of rings across marker shapes. **c** Deformation metrics and prediction

performance. **c**(i) Mean RMSE under different indenter shapes, averaged across all marker types. **c**(ii) RMSE values for different indenter shapes across three types of concentric ring markers. **c**(iii) Overall mean change in Hu moments (ΔH) under different marker shapes. **d** Representative real VTS images of concentric ring markers under deformation. **d**(i) Concentric circular markers before and after deformation. **d**(ii) Concentric hexagonal markers before and after deformation. **d**(iii) Concentric pentagonal markers before and after deformation.

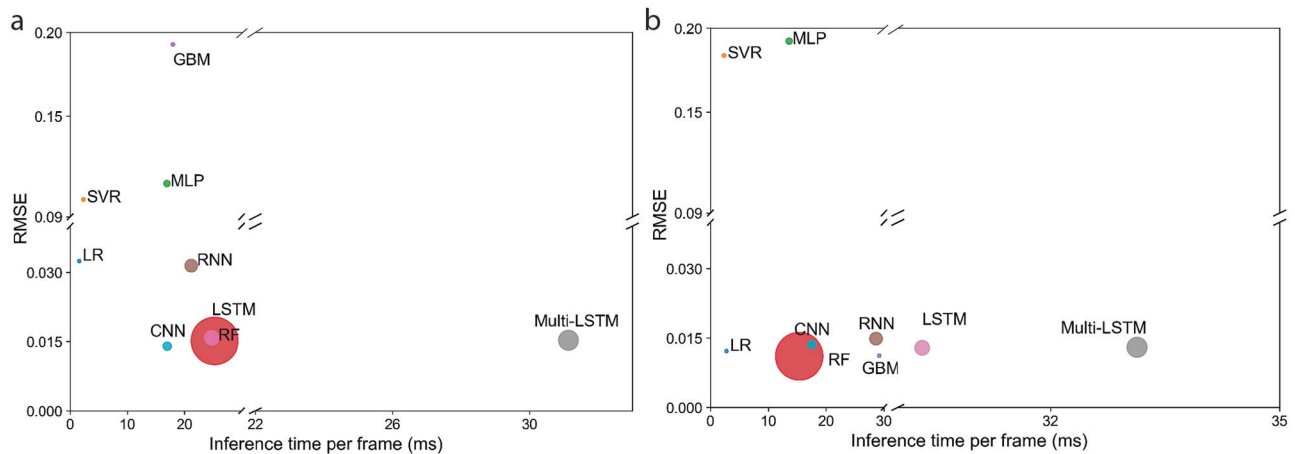


Fig. 6 | Trade-off between inference speed and prediction accuracy across learning algorithms. a Normal force estimation using distributed markers. **b** Normal force estimation using concentric-ring markers. Each panel shows the relationship between inference time per frame (x-axis) and prediction error (RMSE, y-axis) for different learning algorithms. Bubble area represents the corresponding training time, indicating computational cost during model optimisation. A broken-

axis layout is adopted to visualise models with substantially different inference speeds and error ranges within a single view. Learning algorithms include Linear Regression (LR), Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting Machine (GBM), Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short-Term Memory network (LSTM), Multi-layer LSTM (Multi-LSTM), and Convolutional Neural Network (CNN).

summarised in Fig. 6. Specifically, Fig. 6a reports the normal-force results for distributed markers, while Fig. 6b shows the corresponding performance for concentric-ring markers.

For the distributed markers, input features consisted of the displacements and area-change values of every individual marker, yielding a high-dimensional description of the deformation field. In contrast, the concentric-ring markers were represented by a compact set of Hu-moment descriptors that capture the global, radially symmetric deformation of the entire ring structure. This replacement of numerous local sampling nodes by a small number of global deformation descriptors is central to the MIE framework and embodies its emphasis on computational efficiency.

As shown in Fig. 6a, under normal loading with distributed markers, high accuracy is achieved primarily by deep architectures such as CNNs, which are capable of mining complex features from the irregular, high-dimensional deformation field. Shallow models, including linear regression and SVR, exhibit substantially higher prediction errors, reflecting the difficulty of extracting informative patterns from spatially heterogeneous, node-wise deformation measurements.

In contrast, Fig. 6b reveals a markedly different trend for concentric-ring markers. Tree-based ensemble models (RF, GBM) already surpass the CNN baseline, and even a simple linear model achieves accuracy comparable to that of deep architectures. These results demonstrate that the concentric-ring representation encodes the dominant deformation mode so explicitly that shallow models with few trainable parameters can reach or even exceed the performance of data-hungry deep networks.

This behaviour highlights a key advantage of the MIE paradigm: by embedding the global deformation geometry directly into the physical marker design, the sensor off-loads a significant portion of feature-extraction complexity from the learning algorithm. Compared with the node-wise, spatially heterogeneous deformation sampling of distributed markers, the concentric-ring layout provides a low-dimensional, deformation-aligned representation that is inherently smoother, less noisy, and more data-efficient. Such geometry-aware encoding not only simplifies marker tracking-reducing the difficulty of detecting and following individual markers-but also lowers the complexity of regression-stage feature extraction, thereby reducing the overall computational cost.

This design-driven information encoding exemplifies the principle of Embodied Intelligence, wherein sensing capability arises from the coupling between the sensor's physical design and external forces. By jointly leveraging the MIE framework and embodied-intelligence insight, part of the “intelligence” in vision-based tactile sensing is shifted from algorithmic

depth to geometry-aware physical encoding, improving accuracy while minimising computational burden. This synergy is expected to facilitate the development of future real-time, low-latency tactile perception and control systems.

MIE framework: stability under indenter-offset perturbations

In vision-based tactile sensing, the effectiveness of model-based force regression depends on how well the input marker observations represent the underlying elastomer deformation field. These observations provide an observable approximation of deformation process, and reliable force estimation requires that this approximation faithfully captures the true deformation patterns across the sensing surface. We refer to this property as the fidelity of deformation information.

This fidelity becomes particularly important in practical manipulation scenarios, where contacts may occur at arbitrary locations, potentially leading to spatially non-uniform deformation sampling and information loss. We therefore investigate how spatial variations in contact location affect the fidelity of deformation information across different marker configurations.

To isolate the effect of spatial variation, we adopt a controlled experimental setup in which normal forces are systematically applied at predefined locations across the sensing surface. We define central contact as the reference condition (offset = 0) and apply controlled normal forces at different spatial locations (Fig. 7a(i) and b(i)). This setup enables a systematic analysis of deformation-information fidelity while decoupling other factors. More complex manipulation scenarios fall beyond the scope of this study and are left for future investigation.

We quantify RMSE under these conditions as a proxy for the fidelity of deformation information encoding across different contact locations. RMSE reflects how variations in contact position propagate through the learned regression model, revealing the consistency between the deformation patterns captured by the marker configuration and the corresponding force predictions. This allows us to evaluate whether spatial variations degrade the quality of deformation representation, and whether concentric, deformation-aligned markers can better preserve this representation under positional variation.

For distributed markers (Fig. 7a), the RMSE variation follows a distinct trend across four interaction regimes. Figure 7a(ii) presents this variation, while Fig. 7a(i) provides a visual reference for the corresponding offset positions within the marker matrix. The observed regimes are described as follows.

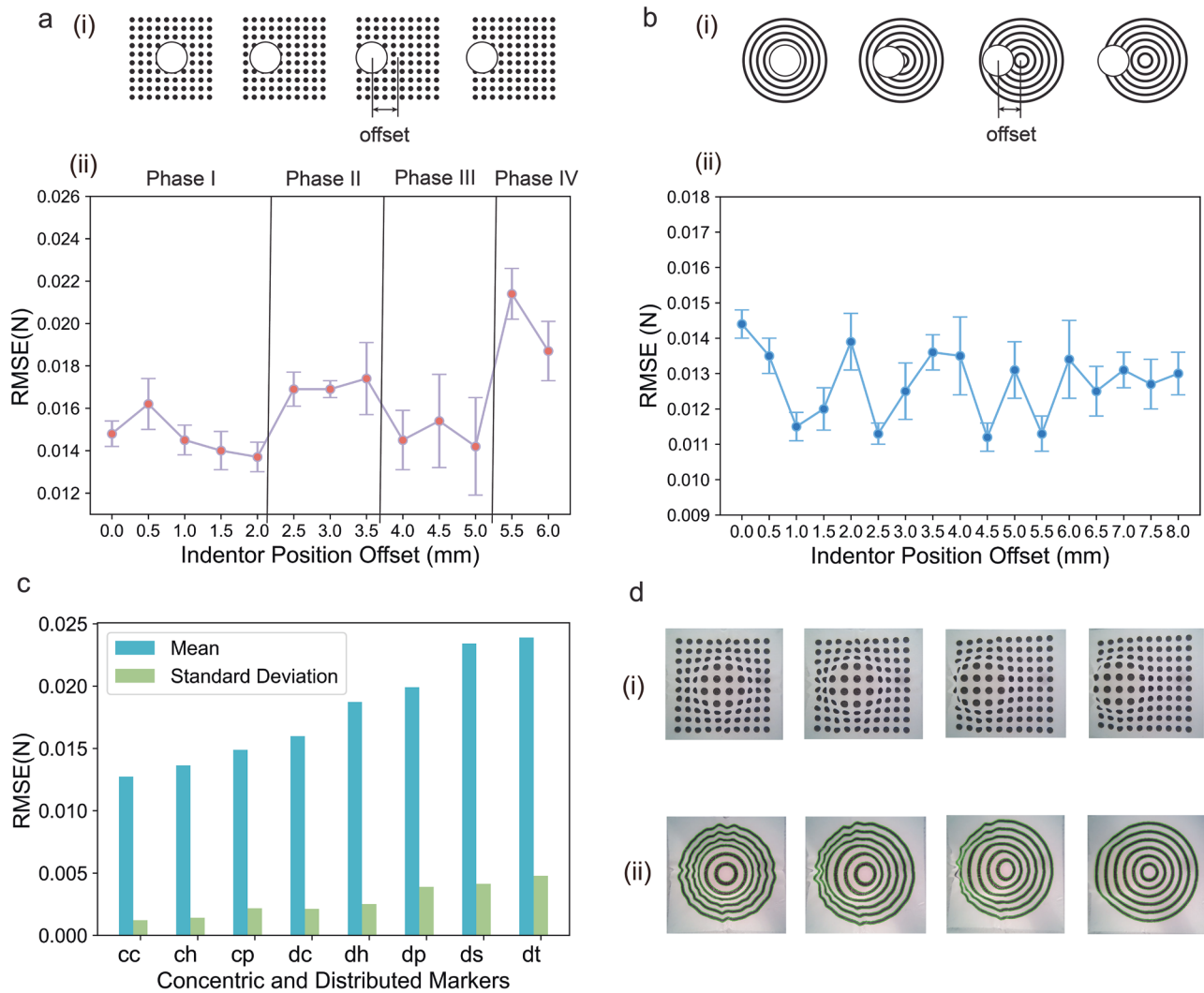


Fig. 7 | Effect of indenter position offset on normal force prediction using distributed markers (dc, dh, dp, ds, dt) and concentric markers (cc, ch, cp). **a** RMSE variations across four interaction phases for distributed markers. **a(i)** Schematic representation of indenter offset relative to the distributed marker matrix, defining four interaction phases. **a(ii)** RMSE as a function of indenter position offset for distributed circular markers (dc), illustrating phase transitions. **b** RMSE variations for concentric markers. **b(i)** Schematic representation of indenter offset relative to the concentric marker structure. **b(ii)** RMSE as a function of indenter position offset

for concentric circular markers (cc), showing an oscillatory pattern with reduced amplitude. **c** Comparison of mean RMSE and standard deviation across different marker configurations. Bar plot of RMSE mean and standard deviation for concentric markers (cc, ch, cp) and distributed markers (dc, dh, dp, ds, dt), highlighting the superior stability of concentric markers. **d** Experimental deformation patterns for distributed and concentric markers. **d(i)** Distributed markers under different indenter positions. **d(ii)** Concentric markers under different indenter positions.

Phase I Initial Stability Region: At small offsets, the indenter's deformation field remains entirely within the marker matrix, ensuring uniform sampling of displacement and area changes. This enables the CNN to achieve high accuracy with minimal RMSE variations.

Phase II Transitional Region: Markers at the indenter's edge undergo higher localised and non-uniform deformation. This perturbs the CNN's learned deformation patterns, resulting in higher RMSE variations.

Phase III Secondary Stability Region: Once the indenter's peripheral deformation field extends beyond the region sampled by the marker matrix, the previously observed localised and non-uniform deformation at the indenter edge diminishes. The remaining markers now undergo a more spatially consistent deformation, reducing irregularities and noise in the input data. This stabilization improves the CNN's ability to extract representative global deformation features, thereby enhancing predictive consistency and resulting in a reduction in RMSE.

Phase IV Data Loss Regime: A significant portion of the indenter-induced deformation occurs outside the marker matrix, leading to

incomplete deformation capture and a substantial decline in CNN prediction accuracy.

The concentric marker configuration exhibits a distinct response to indenter position shifts compared to distributed markers. As shown in Fig. 7b(ii), RMSE variations follow a regular oscillatory pattern with reduced amplitude, indicating a more stable and predictable deformation pattern. The periodic RMSE pattern may be attributed to the inherent ring structure, where indenter displacement interacts with different concentric regions, inducing predictable variations in deformation features.

To further investigate the effect of indenter position offset on normal force prediction, we compared the performance of distributed and concentric markers using two statistical measures: mean RMSE (accuracy) and its standard deviation (stability). Lower mean RMSE reflects higher overall accuracy, whereas a smaller standard deviation indicates more consistent performance across offset positions.

As shown in Fig. 7c, circular markers consistently exhibit the lowest RMSE, reaffirming their effectiveness in capturing deformation characteristics for force prediction. Among the three concentric marker

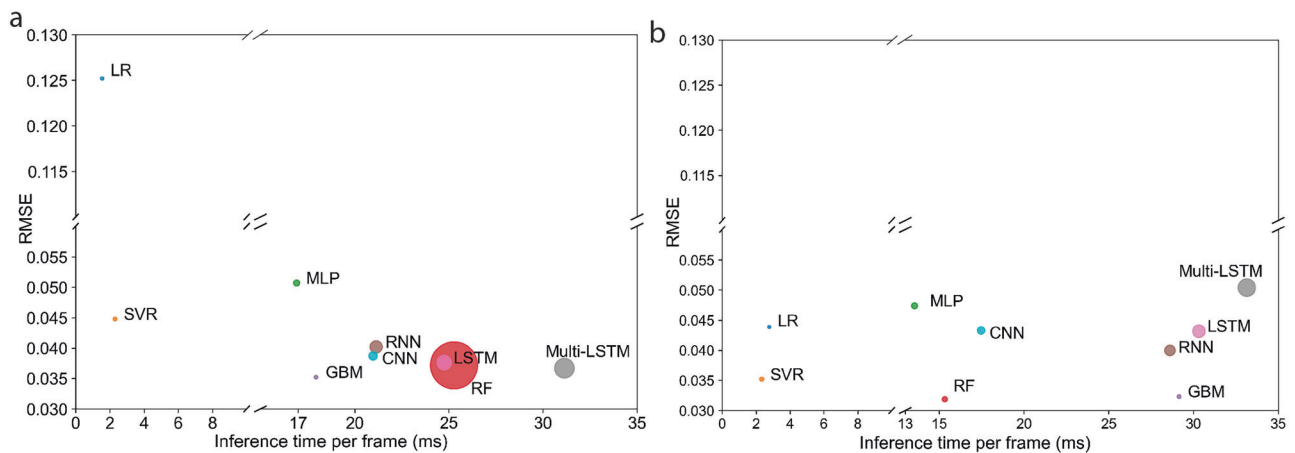


Fig. 8 | Trade-off between inference speed and prediction accuracy across learning algorithms. a Shear force estimation using distributed markers. **b** Shear force estimation using concentric-ring markers. Each panel shows the relationship between inference time per frame (x-axis) and prediction error (RMSE, y-axis) for different learning algorithms. Bubble area represents the corresponding training time, indicating computational cost during model optimisation. A broken-axis

layout is adopted to visualise models with substantially different inference speeds and error ranges within a single view. Learning algorithms include Linear Regression (LR), Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting Machine (GBM), Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short-Term Memory network (LSTM), Multi-layer LSTM (Multi-LSTM), and Convolutional Neural Network (CNN).

configurations, concentric circular markers (cc) achieve the lowest RMSE, providing the most stable global deformation representation. Similarly, among the five distributed marker configurations, distributed circular markers (dc) perform best, achieving the lowest RMSE within this category. This trend persists across both marker types, confirming that layouts with stronger deformation-alignment correlates with lower predictive errors.

For the distributed configuration, we adopted the standard grid layout used in the earlier density-fill-factor study, fixing the marker spacing and adjusting the marker size to achieve the previously recommended 15% fill-factor window. To ensure a fair comparison, the concentric-ring layout was fabricated with the same overall 15% fill-factor and implemented as a representative six-ring design lying within the RSS-derived recommended operating window of approximately 5–7 rings, without further optimisation of ring count. Under these controlled conditions, layouts with stronger alignment to the dominant deformation mode—most notably the concentric configurations (cc, ch, cp)—exhibited lower mean RMSE and smaller standard deviations across positional offsets. These results indicate that: stability in force-estimation improves as the marker geometry better aligns with the dominant deformation mode.

Figure 7d further illustrates these findings with experimental deformation patterns under varying indenter positions. For distributed markers (i), deformation becomes less consistent with larger offsets, particularly near the boundaries, where certain markers undergo substantial area changes and non-uniform displacements, leading to localised instability and disrupting global symmetry. This spatial inconsistency aligns with the observed increase in RMSE and reduced prediction stability. In contrast, concentric markers (ii) maintain radially symmetric and continuous deformation across all positions. Even at the maximum offset (rightmost image), the rings deform in a smooth and uniform manner, highlighting their robustness and ability to generalise under non-central contact conditions.

These results highlight a complementary advantage of the deformation-aligned MIE framework. While the previous section demonstrated that MIE reduces the computational burden of feature extraction by embedding global deformation geometry into the marker design, the present offset study reveals that the same alignment principle also enhances prediction stability under spatially varying contacts. By providing a global, low-dimensional basis aligned with the dominant deformation mode, MIE mitigates the sensitivity of force estimation to positional perturbations. This stability advantage is particularly valuable for practical deployment, where indenter or object contacts are rarely perfectly centred. Leveraging both efficiency and stability, deformation-aligned markers can support real-time,

low-latency tactile perception and control in unstructured manipulation scenarios, extending the utility of vision-based tactile sensing beyond controlled laboratory conditions.

MIE framework: regime-dependent model performance under shear loading

The preceding results establish the MIE framework under normal-force-dominated interactions, where spatially heterogeneous surface deformation makes marker geometry and distribution critical for force estimation, stability, and contact-shape perception. However, robotic manipulation frequently involves loading conditions beyond pure normal contact, including shear forces. These interactions introduce a fundamentally different deformation regime, in which the dominant informative signal shifts from localised surface deformation to collective marker displacement. Within the MIE framework, this domain transition raises the question of whether the marker-design principles identified under normal loading remain applicable when shear forces dominate the interaction. To address this, we next extend the MIE framework to shear-dominated force estimation.

In contrast to the normal-force regime, a markedly different trend emerges under shear loading. As shown in Fig. 8, Support Vector Regression (SVR) consistently outperforms deep neural networks (e.g., CNNs) in terms of overall performance, considering prediction accuracy, inference latency, and training time jointly. This indicates that, under shear-dominated interactions, simpler models are not only sufficient but also preferable.

This behaviour reflects a fundamental change in the information-carrying mechanism of the marker field. Unlike normal loading, where deformation is spatially heterogeneous and requires models to extract complex local patterns, shear loading predominantly induces coherent, global lateral translation of the marker array. As a result, the informative signal is largely low-dimensional and highly structured, reducing the need for deep feature hierarchies. In this regime, the inductive bias of SVR toward smooth, low-complexity mappings becomes particularly well suited to the underlying physical process.

Furthermore, the superior computational efficiency of SVR—manifested in both faster training and lower inference latency compared with CNNs—highlights that model complexity is no longer the performance bottleneck under shear loading. Instead, the dominant deformation mode itself simplifies the learning task, allowing lightweight models to achieve strong generalisation. This contrasts sharply with the normal-force regime, where complex, non-uniform deformation necessitates deeper architectures.

These results reveal a regime-dependent role of learning models within the MIE framework: while deformation-aligned marker designs can off-load complexity from deep networks under normal loading, shear-dominated interactions intrinsically constrain the deformation manifold, making shallow models inherently sufficient. This observation further underscores that optimal model choice is fundamentally governed by the dominant deformation mode, rather than model capacity alone.

Domain-specific effects of marker design for shear force estimation

We evaluated shear force estimation under preloaded normal forces across multiple preload levels, spanning both slip and no-slip regimes. Two marker-design families were assessed in parallel: (i) distributed marker arrays and (ii) concentric ring markers. In both cases, shear forces were applied under controlled normal preload, and force estimation was performed using the same modelling pipeline and evaluation protocol as in the normal-force experiments, enabling a direct comparison of design sensitivity across force modalities.

Across all preload conditions, shear force estimation exhibits a markedly reduced sensitivity to marker shape for both marker families. Unlike the normal force results (Figs. 4 and 5), where marker geometry leads to clear separation in prediction accuracy, the shear force RMSE values associated with different marker shapes remain within a narrow range under each preload condition. No consistent ordering or systematic performance distinction among marker shapes is observed for either distributed markers or concentric ring markers, indicating that under shear-dominated loading, prediction accuracy is weakly dependent on marker shape within each design family.

Despite this shared insensitivity to shape variations, a systematic difference emerges at the family level. Across preload conditions, deformation-aligned concentric ring markers achieve a consistently lower shear force RMSE, remaining in the range of approximately 0.03–0.04 N, whereas distributed markers exhibit a higher RMSE band of ~0.04–0.05 N. This performance gap persists across slip and no-slip regimes and does not diminish with increasing normal preload.

These results are consistent with a qualitative difference in the dominant deformation patterns induced by shear and normal loading. Under normal force, deformation is spatially heterogeneous, and variations in marker shape and structure strongly influence how local deformation features are encoded. In contrast, shear loading primarily produces in-plane deformation characterized by coherent lateral displacement of the marker field shown in Fig. 9b(iii). In this regime, shear force estimation is largely governed by collective marker movements, which reduces sensitivity to marker-specific geometric features while preserving sensitivity to the global organization of the marker pattern.

Marker distribution effects under shear-dominated loading

While the above results examine the influence of marker design under shear-dominated loading, MIE framework also emphasizes the role of marker distribution in shaping sensing performance. We therefore next evaluate how marker density and fill factor affect shear force estimation and computational cost.

Figure 9d examines the influence of marker distribution parameters, including marker density D and fill factor ϕ , on shear force estimation performance, inference time, and the combined cost metric under shear-dominated loading. Across all tested conditions, shear force RMSE exhibits weak sensitivity to both marker density and fill factor, with variations remaining comparable to trial-to-trial variability (Fig. 9d(Ai), (Bi), (Ci)). No monotonic trend in shear prediction accuracy is observed with changing marker density or fill factor, indicating that, within the tested range, variations in marker distribution parameters have a limited effect on shear force estimation performance.

This weak dependence is consistent with the underlying deformation mechanism under shear loading. Unlike normal-force interactions, which induce spatially heterogeneous out-of-plane deformation, shear loading

primarily generates coherent in-plane displacement of the marker field. As a result, shear force estimation is governed predominantly by collective marker movements rather than by fine-grained spatial sampling of local deformation, reducing sensitivity to both marker density and marker size.

In contrast, inference time increases systematically with marker density (Fig. 9d(Aii), (Cii)), reflecting the increased number of tracked features and associated computational overhead. Inference time shows minimal sensitivity to fill factor (Fig. 9d(Bii)), as marker size does not alter the number of tracked points. Consequently, the combined cost metric increases with marker density (Fig. 9d(Aiii), (Ciii)), while remaining approximately constant across fill factor variations (Fig. 9d(Biii)). These trends indicate diminishing returns from increasing marker density under shear loading, as computational cost rises without a corresponding improvement in prediction accuracy.

Overall, these results demonstrate that, under shear-dominated interactions, marker distribution parameters primarily affect computational efficiency rather than sensing performance. A moderate marker density is therefore sufficient to achieve reliable shear force estimation, and further increases in density mainly incur additional computational cost. This behaviour contrasts with the normal-force regime, where marker distribution plays a more critical role in encoding spatially heterogeneous deformation, highlighting the domain-specific nature of marker design optimisation.

Discussion

Marker Information Efficacy (MIE) formulates marker design as a deformation-information encoding problem, capturing how force-induced deformation in soft elastomeric interfaces is represented through marker observations. This study introduces MIE as a design-centric framework for optimising marker geometry, size, and spatial distribution.

Within this framework, marker design is governed by two key principles: (i) deformation-information encoding, which extends beyond displacement through the incorporation of area change—coupled with marker geometry (shape and size)—and spatial distribution; and (ii) a principled marker redesign strategy, in which marker configurations are systematically adapted to align with dominant deformation modes under different sensing conditions.

Our findings show that circular markers tend to outperform other marker shapes in force estimation tasks, highlighting their ability to enhance sensing accuracy and robustness. Crucially, the framework provides a principled basis for rational marker design across different sensing scenarios. Together, these findings establish marker design as a fundamental determinant of VTS performance and position MIE as a general framework for marker-based tactile sensing.

To ground the MIE framework in measurable deformation behaviour, we first analyse the dominant deformation patterns captured by distributed markers. Principal component analysis (PCA) on distributed markers indicates that a circular-shaped first principal component captures more than 95% of the soft tissue deformation information. Together with Residual Sum of Squares (RSS) fitting, which consistently shows lower error for circular markers, these results confirm that circular geometry efficiently represents dominant deformation information. This insight directly motivates the design of concentric-ring markers that explicitly align with the global radial symmetry of soft tissue deformation. To quantify their deformation, we employed Hu moments, which provide compact descriptors of how concentric rings deform under loading. Building on this quantitative representation, the concentric-ring configuration enables highly accurate force prediction (RMSE = 0.011 N), demonstrating the effectiveness of deformation-aligned marker design. By explicitly aligning marker geometry with the dominant deformation modes, concentric rings preserve deformation information more efficiently and improve prediction robustness. Moreover, owing to their continuous marker topology, concentric-ring markers require substantially fewer descriptors than conventional distributed marker configurations, enabling accurate force prediction using lightweight models (e.g.,

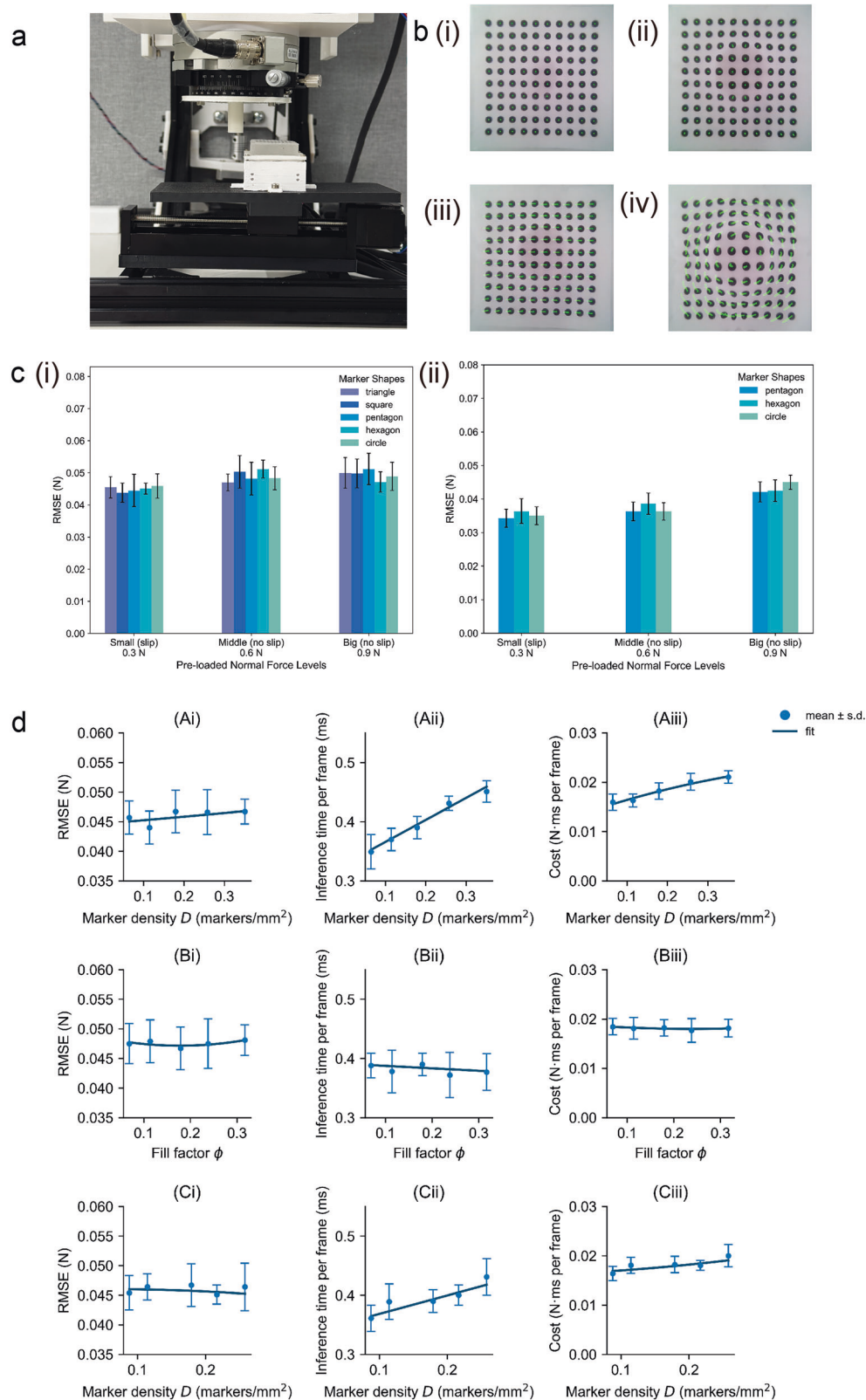


Fig. 9 | Shear-dominated force estimation under preloaded normal forces.

a Experimental setup for shear force data collection, where lateral motion is applied after establishing a constant normal preload. **b** Representative marker deformation under different loading conditions: (i) unloaded state, (ii) pure normal loading, (iii) shear loading under normal preload, and (iv) torsional loading under normal

preload. **c** Shear force estimation RMSE (mean $\pm$ s.d.) for different marker shapes under three normal preload levels (0.3, 0.6, and 0.9 N), spanning slip and no-slip regimes, for (i) distributed markers and (ii) concentric ring markers. **d** Trade-offs between accuracy and computational efficiency across controlled density variations under shear-dominated loading.

LR and SVR) while reducing computational cost, which is particularly advantageous for real-time tactile sensing.

The contribution of this work extends beyond identifying the superiority of specific marker geometries. Marker configurations can be systematically derived by analysing deformation information and aligning marker structures with dominant deformation modes. Concentric-ring markers serve as a representative example of deformation-aligned design for normal-force-dominated interactions, where the dominant deformation pattern is radial. By embedding this structure directly into marker geometry, the resulting representation becomes more compact and low-dimensional, reducing the reliance on complex models.

More broadly, this principle suggests that other interaction regimes—such as shear or anisotropic contact—may favour alternative marker structures that align with their respective deformation characteristics. Accordingly, MIE establishes a general methodology for deriving marker configurations from deformation behaviour, rather than prescribing a single optimal design. This perspective provides a unifying lens through which the following analyses can be interpreted.

Beyond shape, our results show that performance is also governed by the distribution of markers. Density and fill factor act as coupled variables: sparse layouts undersample deformation, while excessive coverage leads to merging and instability. Strikingly, an intermediate regime—around 10–20% in both density and fill factor—consistently minimised error while keeping computational effort manageable. Within the MIE framework, these variables are elevated from incidental fabrication parameters to explicit design factors. This shift underscores that computational efficiency in tactile sensing arises not only from marker geometry but also from balanced sampling of deformation. In doing so, it offers a principled route for future VTS research that preserves both accuracy and efficiency.

To further delineate the domain of applicability of the proposed principles, we examined how the informational role of marker design varies across distinct deformation regimes. Together, the normal and shear force experiments suggest that the effectiveness of marker design within the MIE framework is fundamentally governed by the dominant deformation mode of the elastomeric layer. Under normal loading, deformation is spatially heterogeneous and involves localised, non-uniform out-of-plane strain. In this regime, marker properties such as shape, size, density, and structured arrangements directly influence how deformation patterns are encoded into visual features, leading to substantial gains in estimation accuracy, stability, and robustness. Marker distribution therefore plays a central role in determining both sensing performance and the trade-off between accuracy and computational cost.

In contrast, shear loading predominantly induces coherent lateral displacement of the marker field. Here, the primary information carrier shifts from marker-specific geometric features to collective marker movement, resulting in a markedly reduced sensitivity to local marker shape and distribution parameters. Within the tested range, variations in marker density and fill factor yield only marginal changes in shear estimation accuracy, while primarily affecting computational cost through the number of tracked features. This behaviour indicates that, under shear-dominated interactions, marker distribution governs efficiency rather than informational content.

The consistently higher shear estimation accuracy achieved by concentric ring markers indicates that deformation-aligned markers can nevertheless improve robustness by providing continuous and redundant representations of collective motion. Overall, these findings suggest a principled, domain-dependent interpretation of the MIE framework: marker-property-dominated designs are most effective for regimes characterized by spatially heterogeneous deformation, whereas marker-movement-dominated regimes place greater emphasis on global structural coherence and efficient representation of collective displacement.

The results presented above are derived under controlled indenter-based contact conditions, yet they reveal a fundamental aspect of vision-based tactile sensing: the accuracy of force estimation is intrinsically linked to the quality of deformation information encoding. This controlled setup

can be understood as a minimal and interpretable abstraction of real manipulation scenarios, where contact conditions are typically more complex and involve normal, shear, torsional, and sliding interactions. In this context, shear corresponds to tangential deformation under lateral loading without macroscopic relative motion, whereas slip denotes the transition to relative motion once the frictional limit is exceeded.

Extending this perspective to more complex interaction modes, deformation induced by torsional and sliding forces exhibits distinct spatial and temporal characteristics that further challenge consistent deformation encoding. Torsional moments tend to induce larger shear deformation toward the boundary of the contact region, where the effective moment arm is larger, rather than being concentrated at the centre of the contact region (not shown in this paper). From a deformation perspective, torsional moments can be interpreted as spatially varying shear fields, giving rise to rotational patterns of collective marker displacement, as illustrated in Fig. 9b. Sliding interactions further introduce transient deformation patterns with rich temporal characteristics. Dynamic sliding can be regarded as a temporally varying shear process, characterised by sustained or intermittent collective marker motion. A systematic investigation of these torsional and sliding-induced deformation regimes, including their temporal signatures and deformation symmetries, is beyond the scope of the present study and will be explored in future work.

Building on this physical interpretation of deformation representation, it is also important to clarify how these findings should be understood from a generalisation perspective. The evaluation in this work was conducted under controlled indentation conditions with predefined indenter geometries, which were intentionally designed to isolate the effect of marker design on deformation-information encoding. Accordingly, the reported RMSE reflects the fidelity with which different marker configurations encode the deformation field within a given contact regime and map it to force, rather than their ability to generalise across arbitrary contact geometries. Within this scope, the consistent performance observed across different indenter geometries indicates that the proposed deformation-information encoding remains stable across contact geometries within a shared physical deformation regime.

Beyond this consistency across known contact geometries, we further performed a Leave-One-Indenter-Out Cross-Validation (LOIO-CV) experiment as a more stringent validation of the proposed MIE framework. In this protocol, each indenter geometry was excluded entirely from training and used exclusively for testing, thereby evaluating the framework on previously unseen contact geometries. The framework maintained consistently high prediction performance across all held-out geometries (Supplementary Note S5), demonstrating that the deformation-information encoding established by the proposed MIE framework remains effective even when transferred to unseen indenter geometries within the same physical deformation regime. Although this experiment is presented as supplementary, it provides additional evidence that the proposed framework possesses not only physical consistency across known contact conditions but also robustness to previously unseen contact geometries.

Deformation-information fidelity directly governs the quality of the visual features extracted from marker observations. Higher fidelity leads to visual features that are more informative, less noisy, and more representative of the underlying deformation field, thereby enabling a more stable and less ambiguous mapping between observed deformation and applied force. Consequently, the quality of deformation representation fundamentally determines the achievable accuracy of force estimation.

A key factor underlying this fidelity is the inclusion of marker area change in the deformation representation. While marker displacement captures in-plane motion, it provides only a partial observation of the deformation field, particularly under normal loading where out-of-plane compression dominates. By incorporating area change, the representation becomes sensitive to local volumetric deformation, enabling a more complete encoding of the underlying deformation field. This is particularly critical for normal-force estimation, where the force-deformation

relationship is governed by compressive mechanics rather than purely lateral motion.

Beyond the inclusion of area change as a feature, its effectiveness is inherently shaped by marker design itself. Specifically, geometric attributes such as marker shape, size, and spatial distribution directly influence how area change manifests under the same loading condition. For instance, markers with smooth and symmetric boundaries, such as circular geometries, tend to undergo more uniform and continuous area variation under normal compression, resulting in stable and low-noise deformation descriptors. In contrast, markers with sharp edges or anisotropic geometries introduce localised strain concentrations, leading to irregular and spatially heterogeneous area-change patterns.

Marker size further modulates this behaviour by defining the spatial scale at which deformation is sampled. Larger markers tend to average local deformation, potentially smoothing out fine-grained variations, whereas smaller markers provide higher spatial resolution but are more susceptible to tracking noise and instability. Similarly, marker distribution determines the sampling density of the deformation field, affecting how completely area-change information captures the global deformation structure.

As a result, area change should not be understood as an isolated feature, but as a deformation descriptor whose informativeness is intrinsically governed by marker design. This highlights that the quality of deformation representation arises from the coupling between feature definition and physical marker configuration, rather than from feature selection alone.

This more physically informative representation also helps explain the low RMSE observed in our experiments. By capturing both in-plane motion and out-of-plane compression, the marker representation reduces ambiguity in the mapping between observed deformation and applied force, leading to a more stable and consistent regression relationship. Consequently, variations in contact geometry introduce less variability in the encoded deformation features, resulting in improved prediction accuracy and lower RMSE.

From an evaluation perspective, it is important to clarify how the reported RMSE relates to the underlying sources of error in the measurement and modelling process. The force sensor exhibits random noise, characterised by a standard deviation of approximately 0.007 N, as well as quantisation effects arising from its 0.01 N resolution, corresponding to an uncertainty of approximately ± 0.005 N. The random noise introduces continuous fluctuations in the measured signal, while the quantisation limits the smallest distinguishable change in force. Together, these factors define the effective uncertainty of the reference measurement, setting a practical lower bound on the observable error.

The achieved RMSE of 0.011 N lies within the same order of magnitude as this measurement uncertainty. This suggests that the prediction error is approaching the level at which it becomes comparable to the inherent uncertainty of the reference signal, indicating that further improvements may be increasingly limited by the measurement resolution. This observation indicates that the achieved accuracy is bounded by the resolution of the measurement system, rather than suggesting that the model exceeds the physical sensing capability.

The observed performance cannot be attributed to overfitting to a specific data distribution. Across multiple indenter geometries with distinct contact shapes, the RMSE remains consistently stable, indicating that the model captures a shared underlying deformation-force relationship rather than memorising geometry-specific input patterns. This observation is further supported by Fig. 4b and Fig. 5c, where, for the same marker shape, the RMSE values remain at a comparable magnitude across different indenter shapes. This similarity in error level suggests that the learned mapping is not driven by indenter-geometry-specific fitting, but instead reflects a consistent relationship between deformation and force.

This behaviour is consistent with the physical structure of the deformation field, in which displacement and area change jointly encode the dominant deformation modes. As these features provide a physically grounded and consistent representation of deformation across different contact conditions, the resulting regression becomes less sensitive to

variations in contact geometry. Consequently, the RMSE should be interpreted as arising from a physically informative and consistent deformation representation, rather than as an artefact of overfitting.

Following the clarification of RMSE interpretation, we provide a complementary perspective by examining deformation feature representation at the level of visual features. Learned feature representations, such as those obtained using CNNs or Vision Transformers, offer a flexible mechanism for extracting task-relevant features directly from raw observations, enabling the modelling of complex, spatially heterogeneous, and nonlinear deformation patterns without predefined descriptors.

In contrast, the MIE framework approaches deformation representation through the coordinated marker design and physically grounded feature descriptors. In this work, centroid displacement, area change, and Hu moments are selected as structured features corresponding to distinct aspects of the deformation field, including in-plane marker motion, local compression, and global shape variation, where centroid displacement quantifies lateral (in-plane) motion of markers, area change captures local volumetric compression induced by normal loading, and Hu moments encode global shape deformation and symmetry variations of the marker structure. These descriptors can be interpreted as projections onto physically meaningful deformation components.

From a feature engineering perspective, these two approaches differ in how feature representational complexity is handled. Learned features concentrate this complexity within the model, allowing flexible adaptation to diverse deformation patterns, albeit typically with a higher computational burden due to the need to jointly learn marker detection, deformation structure, and force estimation from high-dimensional inputs. In contrast, the MIE framework redistributes part of this complexity to the joint design of marker structures and feature representations, encoding deformation information prior to learning. This enables the use of compact, physically grounded representations and simpler models, while preserving alignment with the underlying deformation physics. Such a design reflects a central objective of the MIE framework, namely to reduce computational complexity through marker design and physically grounded feature selection.

These two representations—learned and physically grounded features—reflect fundamentally different feature extraction approaches to modelling deformation information. Physically grounded features provide a controlled and transparent representation of the deformation field, enabling the effect of marker design to be isolated. This controlled representation helps ensure that the observed performance differences can be primarily attributed to marker design rather than feature selection. While learned representations may capture richer visual information, they also introduce additional modelling complexity, making it difficult to disentangle the respective contributions of feature representation learning and marker design.

A systematic comparison between these two representation strategies would be valuable for further understanding their respective roles in deformation representation, force estimation, and computational efficiency. However, such an investigation lies beyond the scope of the present study, which focuses specifically on the role of marker design and physically grounded feature construction within the MIE framework, and will be explored in future work.

Several recent studies adopt continuous marker patterns (CMP) that encode deformation through dense textures and track features such as corners or color junctions instead of discrete marker centroids^{39–42}. These approaches improve tracking robustness under large deformation by increasing local feature redundancy and reducing sensitivity to centroid drift, perspective effects, and partial occlusion. From the perspective of the proposed MIE framework, CMP can be interpreted as a high-density, redundancy-driven encoding strategy, where deformation information is distributed across a large number of marker features like corners and lines. In contrast, the proposed concentric ring markers represent a deformation-information-encoding paradigm, in which global, structured geometry is deliberately introduced to match the dominant deformation modes of the elastomeric layer.

Rather than relying on dense marker features, concentric rings transform spatially heterogeneous deformation into low-dimensional, globally coherent geometric variations, enabling stable and efficient inference with substantially reduced feature dimensionality. Under this interpretation, CMP corresponds to a limiting case of MIE where effective marker density approaches continuity, whereas concentric ring markers occupy a different region of the MIE design space that prioritizes information efficiency and structural alignment over feature redundancy. Importantly, this distinction explains why concentric ring markers achieve strong performance even at moderate fill factors and marker densities, while CMP-style designs typically require dense patterns and more complex tracking pipelines to achieve similar robustness. A systematic comparison between redundancy-driven continuous patterns and deformation-aligned markers under matched conditions remains an important direction for future investigation. Further conceptual illustrations and extended discussion of this interpretation are provided in Fig. S2.

A fundamental design tension in vision-based tactile sensors (VTS) lies in the trade-off between marker-based force sensing and markerless surface perception^{21,22}. Opaque markers provide strong cues for tracking deformation, tangential displacement, and force, but inevitably occlude geometric features required for object and texture recognition. In contrast, markerless tactile skins preserve surface detail but offer weaker sensitivity to shear-related deformation and force encoding. This trade-off has been widely acknowledged in prior work and represents a core challenge in visuotactile sensor design²³. In this study, the proposed MIE framework focuses on force-oriented deformation encoding, and therefore does not explicitly optimize for surface reconstruction quality. This reflects a deliberate scoping of objectives rather than an exclusion of visibility considerations. Within MIE, contact visibility is bounded through physically interpretable design variables—marker density and fill factor—which directly govern the degree of optical occlusion. The emergence of an optimal intermediate regime (~10–20% surface coverage) reflects a balance between deformation sampling fidelity and optical occlusion, providing a practical operating window that preserves sufficient optical pathways for surface cues while avoiding excessive marker interference.

Importantly, MIE should be viewed not as a prescriptive optical implementation, but as a design-centric evaluation framework that defines a design space over which multiple sensing objectives can be optimized. Within this space, force estimation accuracy, computational efficiency, deformation stability, and surface visibility can be treated as coexisting and potentially competing objectives.

Recent studies employing visibility-modulated markers further support this interpretation. For example, UV-based or switchable marker designs, such as UVtac^{43,44}, demonstrate that markers need not be permanently visible to the imaging system: markers can be selectively activated under specific illumination conditions to enable force and shear estimation, while remaining effectively invisible during surface or texture perception. Such approaches, including UV-only markers and illumination-dependent switching schemes, alleviate the classical marker-markerless trade-off by decoupling force encoding from geometric visibility. Along similar lines, recent advances such as translucent or tinted marker designs, such as MagicSkin²², further demonstrate that this trade-off can be softened by modulating marker visibility rather than eliminating markers altogether. These approaches—UV-activated, switchable, or translucent markers—should be understood as different instantiations along a common design dimension of optical visibility modulation. Within this context, translucency-aware or visibility-preserving marker designs can be naturally incorporated into the MIE framework as additional design dimensions, enabling multi-objective optimisation across force estimation accuracy, computational efficiency, deformation stability, and surface visibility. This perspective positions MIE as a general and extensible framework capable of accommodating diverse optical implementations while providing a principled basis for rational visuotactile sensor design. Figure S3 provides the overview and illustrative examples of visibility modulation strategies within the MIE framework.

Elastomer softness and surface geometry influence visuotactile sensing primarily by modulating the amplitude of the deformation field transmitted to the marker layer under both normal and shear loading. Under force-controlled conditions, variations in elastomer hardness act predominantly as a gain factor: softer substrates produce larger deformation amplitudes, whereas stiffer substrates yield attenuated responses under identical applied forces. This amplitude modulation primarily rescales the deformation field without substantially altering its dominant spatial organisation (e.g., radial expansion or coherent in-plane translation), which remains qualitatively stable across hardness levels for both loading modes. Surface geometry further modulates deformation by shaping force transmission and mechanical boundary conditions. While planar and gently curved (e.g., spherical) surfaces largely preserve uniform deformation patterns, more anisotropic geometries such as cylindrical surfaces bias force transmission and constrain deformation pathways in a direction-dependent manner, leading to systematic, geometry-dependent shifts in deformation amplitude and spatial projection onto the marker layer. From the perspective of the MIE framework, elastomer softness and surface geometry therefore function as upstream mechanical factors that regulate the magnitude and spatial projection of the deformation field delivered to the marker layer, rather than the deformation organisation that carries information. Figure S4 presents the experimental design and supplementary visual evidence contextualising these mechanical effects within the MIE framework.

In addition to the upstream mechanical factors discussed above, such as elastomer softness and surface geometry, marker fabrication stability and environmental conditions also constitute important upstream factors in VTS sensing. Variations in printing precision, illumination stability, and temperature can influence the fidelity and repeatability of the visual deformation signal formed at the marker layer. Within the MIE framework, these manufacturing and environmental factors are treated consistently with mechanical ones: they shape the quality of the upstream signal formation process, rather than directly determining how deformation information is encoded by marker geometry and distribution. When comparative evaluations are conducted under consistent fabrication and imaging conditions, moderate variations in process or environment primarily manifest as common-mode effects across marker configurations. As a result, they do not alter the relative information encoding efficiency that underpins the design-centric conclusions of the MIE framework, but instead define practical conditions under which such comparisons remain meaningful. Framing process stabilization and environmental robustness as part of the same class of upstream factors therefore extends the scope of the framework without introducing additional design variables at the marker level. These considerations highlight how incorporating material properties, surface geometry, fabrication stability, and environmental conditions into the MIE framework contributes to its conceptual completeness and supports its future applicability across diverse substrates, geometries, and loading conditions.

Taken together, the analyses presented in this section establish MIE as a design-centric framework for vision-based tactile sensing by formalising the marker design space—shape, size, distribution, topology, and visibility modulation—as explicit determinants of how deformation information is encoded. By systematically analysing how these marker properties interact with distinct deformation regimes, MIE provides a broad interpretation that links elastomer deformation, visual feature formation, and learning-based inference through marker-level information encoding, while remaining agnostic to specific material choices, fabrication processes, and optical implementations.

In this view, factors such as elastomer hardness, surface geometry, illumination, and fabrication stability act as upstream conditions that modulate the quality and magnitude of the deformation signal delivered to the marker layer, without changing the central role of marker geometry and distribution in shaping information efficacy. This perspective clarifies why deformation-aligned designs—particularly circular concentric-ring markers—consistently achieve superior accuracy, robustness, and computational efficiency across force estimation. More broadly, MIE shifts part of the

sensing intelligence from model complexity to physical marker design, providing a basis for rational marker selection and principled comparison of marker configurations across diverse visuotactile embodiments. As such, the framework serves not only as an explanatory lens for existing marker-based tactile sensors, but also as a general and extensible reference for systematic marker optimisation in future visuotactile sensing systems.

Methods

Sensor fabrication and imaging setup

The elastomeric sensing unit comprised a multilayer silicone structure embedded with optical markers and laminated onto a transparent acrylic plate. A 1 mm transparent silicone membrane (Ecoflex™ Gel, Smooth-On) formed the deformable top layer, transmitting forces to an underlying marker film. Markers, printed on a flexible transfer sheet using high-resolution graphite printing (sub-100 µm accuracy), were arranged in distributed or concentric-ring configurations, providing high optical contrast and precise geometry. The film was laminated without adhesives, relying on the intrinsic tackiness of silicone, and the entire stack—including a 10 mm silicone support layer—behaved as a mechanically unified body under deformation. To reduce surface tackiness and improve imaging consistency, a light powder coating was applied, minimising reflections and unintended adhesion.

The elastomeric assembly was mounted on a 0.4 mm acrylic base, with only the perimeter sealed by silicone adhesive to prevent air ingress. This hybrid bonding strategy ensured stability and optical clarity while enabling reproducible assembly.

The sensor body consisted of a 3D-printed PLA base and a custom support frame, which secured the elastomeric unit in precise alignment with the optical axis. A 5-MP wide-angle camera (110° field of view) was placed beneath the sensor, capturing deformation images at 20 fps.

Illumination was provided by two white LEDs around the lens, diffused through a translucent acrylic layer to ensure homogeneous lighting and high-contrast marker visibility across deformation states.

Marker design and experimental protocol

Markers are fabricated using high-resolution graphite printing on a flexible, high-contrast transfer film, ensuring accurate geometric shapes and strong optical contrast for reliable visual detection. The fabrication process involves three key steps: (1) Pattern Design: Marker configurations are created in Adobe Illustrator to ensure precise geometry and uniform distribution. (2) Graphite Printing: A high-resolution printer is used to transfer the designs onto flexible transfer paper, generating sharp, high-contrast markers. (3) Lamination: The printed film is carefully adhered to the elastomeric surface, eliminating air bubbles and ensuring strong adhesion. This fabrication method ensures durability, flexibility, and high optical contrast, making the markers ideal for vision-based deformation tracking. To eliminate potential confounding factors, all marker shapes were designed with equal projected area during fabrication, ensuring that performance differences arise solely from geometry rather than size.

During experiments, the tactile sensor was mounted beneath a precision linear stage, while a Robotous six-axis force/torque sensor was used to record the applied forces synchronised with the vision system. The force sensor has a specified force resolution of 0.01 N. Prior to data collection, the sensor was calibrated following the manufacturer's procedure to ensure measurement consistency.

A camera simultaneously captured real-time images of marker deformation under controlled indentation, generating time-aligned datasets that couple visual features with the corresponding force measurements. Synchronisation between the force readings and image acquisition was achieved through a shared acquisition pipeline.

Multiple trials were conducted for each marker configuration under identical hardware and imaging conditions to ensure reproducibility and consistency across experiments.

For distributed markers, displacement (x , y) and area change were extracted from individual markers, whereas concentric-ring markers were

described using Hu moments, providing compact global descriptors of deformation. The resulting datasets were used for regression.

Image acquisition and preprocessing

All images were captured at the native resolution of the camera without any in-camera downsampling or compression. A fixed region of interest (ROI) corresponding to the active marker area was manually defined once for each sensor assembly and kept constant across all trials and marker configurations. This ROI selection was independent of loading conditions and was not adapted during experiments.

Prior to feature extraction, the cropped ROI was resized to a fixed resolution to ensure consistent input dimensionality across experiments and marker designs. Apart from a fixed image resizing step for input normalisation, no additional spatial filtering or explicit denoising was applied. This choice was made deliberately to avoid introducing geometry-dependent or resolution-dependent preprocessing effects that could confound the comparative evaluation of marker designs. Illumination conditions and camera parameters (exposure, gain, frame rate) were held constant throughout all experiments to avoid introducing variability due to imaging artefacts.

Marker features were extracted from the resized ROI images under identical preprocessing settings for all experiments. For distributed markers, displacement in the x - y plane and area change were computed at the marker level; for concentric-ring markers, Hu-moment descriptors were extracted from the full ring structure. In all cases, feature extraction was performed on images with the same spatial resolution, ensuring that differences in model performance arise from marker design rather than preprocessing variations.

Marker geometries were designed such that the pixel-per-marker ratio remained within a narrow and well-resolved range across configurations, avoiding cases where markers became under-resolved or visually merged. Consequently, while absolute force-estimation performance may depend on the specific hardware setup, the relative trends reported in this study—such as the effect of marker shape, density, and fill factor—are evaluated under strictly controlled and consistent imaging conditions and are not tied to a single hardware instance.

The objective of this work is to establish design-centric principles for marker optimisation rather than hardware-invariant benchmarks. Under the fixed preprocessing pipeline described above, all comparative analyses were conducted on a common and controlled basis, ensuring reproducibility and fair comparison across marker designs, and allowing the reported design trends to be expected to generalise across comparable imaging setups that provide sufficient marker resolution.

Data acquisition and sampling protocol

Indentation was applied using a stepper motor operating in a discrete pulse mode. Each command corresponds to a single motor step, which defines the minimum controllable indentation increment. The physical displacement associated with each step is determined by the mechanical transmission system (lead screw pitch and gearing) and is treated as a constant system parameter. In our system, the displacement per step is ~ 0.04 mm. The overall indentation depth is therefore proportional to the cumulative number of motor steps applied over time, ensuring precise and repeatable control of indentation.

A time-discretised control scheme was adopted, in which motor commands were updated at a fixed interval of $\Delta t = 50$ ms. Within each control interval, a variable number of step pulses $u \in [1, 8]$ was issued, corresponding to the number of actuation steps executed per cycle. This results in an effective actuation rate of

$$f_{\text{step}} = \frac{u}{\Delta t} = 20u; \text{ steps/s.} \quad (1)$$

Visual measurements were acquired using a camera at a fixed sampling rate of $f_s = 20$ Hz. The relationship between actuation and sensing is governed by the ratio between the step rate and the sampling rate. Specifically,

each image frame corresponds to approximately u actuation steps:

$$\text{steps per frame} = \frac{f_{\text{step}}}{f_s} = u, \quad (2)$$

or equivalently, each actuation step is observed with a sampling density of

$$\text{frames per step} = \frac{f_s}{f_{\text{step}}} = \frac{1}{u}. \quad (3)$$

This establishes a coupled spatiotemporal resolution between actuation and sensing. At lower actuation rates ($u = 1$), each deformation increment is captured by approximately one image frame, whereas at higher actuation rates ($u = 8$), multiple actuation steps occur within a single frame. Despite this variation, the resulting deformation remains smooth due to the viscoelastic behaviour of the elastomer, ensuring that the observed deformation field remains physically consistent across all operating conditions.

To ensure consistency and reproducibility, all experiments were conducted using an automated data acquisition pipeline. The indentation actuation, image capture, and force measurement were synchronised and executed programmatically, eliminating manual intervention during data collection. This automation ensures that all samples are acquired under identical timing, loading conditions, and sensor configurations, thereby reducing human-induced variability.

Each experimental trial consists of a continuous indentation sequence of fixed duration, yielding approximately N_f image frames per trial at a sampling rate of 20Hz. For each indenter geometry, N_t independent trials were conducted under identical conditions, resulting in approximately N_s samples per indenter.

The total number of samples is determined by the experimental design, including the number of indenter geometries, the number of trials per indenter, and the duration and sampling rate of each trial. In the present study, this design results in every dataset comprising approximately $M = 600$ samples in total, where each sample corresponds to a single time frame with associated marker features and ground-truth force measurement. The applied normal force ranges from 0.01 to 1 N, covering the operational regime of the sensor under controlled indentation conditions.

The dataset used for force regression was randomly divided into 80% training and 20% testing subsets. To avoid sampling bias, comparable numbers of samples were collected for each indenter, providing balanced coverage of the deformation space. This ensures that the reported performance reflects consistent model behaviour across different contact conditions rather than over-representation of specific geometries.

All experiments were conducted under identical actuation and sensing conditions. The combination of discrete step-based actuation, fixed-rate sensing, and automated synchronised acquisition defines a reproducible and statistically controlled sampling protocol, providing a reliable basis for evaluating force-estimation performance.

Data construction: spatial dimension (M)

To construct the input representation for force estimation, the data are organised into an $N \times T$ structure, where N denotes the number of markers and T denotes the number of temporal frames within a fixed observation window. This formulation provides a structured representation of spatio-temporal deformation, enabling a consistent mapping between physical marker behaviour and model input.

The spatial dimension N is defined by the number of markers within the sensing region. During an initial calibration stage, each marker is assigned a unique index according to its spatial location. Owing to the structured matrix layout, this mapping is established deterministically via row-wise and column-wise ordering.

Across frames, index consistency is maintained through a nearest-neighbour association strategy, whereby each detected marker is matched to the closest marker position from the previous frame. This approach leverages the spatial continuity of the deformation field, under which

marker displacements between consecutive frames remain small and locally smooth, allowing reliable approximation of marker identity. Under the controlled indentation conditions considered in this study, all markers remain consistently visible and trackable, and no marker loss is observed, ensuring stable indexing throughout.

Although marker loss does not occur under the deformation regimes considered here, the tracking method is designed to accommodate such cases. In principle, missing markers can be retained within the input structure and handled via imputation or masking strategies without altering the dimensionality of the representation. While not required in the present experiments, this capability enables extension to more challenging scenarios involving occlusion or severe deformation.

Data construction: temporal dimension (T)

The temporal dimension T is defined using a fixed-length window of T consecutive frames, where T is a predefined constant based on experiments. This formulation ensures a bounded input size and avoids unbounded temporal accumulation. The temporal window captures the short-term evolution of deformation without relying on the entire contact history. Image sequences of marker deformation are synchronised with force measurements under controlled indentation conditions.

To ensure temporal consistency across experiments, the indentation process is controlled using a stepper motor, which enables precise and repeatable regulation of indentation speed and duration. A fixed actuation protocol is applied across all trials, such that the temporal evolution of deformation is standardised throughout the dataset. This control minimises temporal variability as a confounding factor, ensuring that differences in the observed deformation are primarily attributable to marker configurations rather than variations in loading dynamics.

Data construction: reference configuration for deformation measurement

Marker displacements are computed relative to a reference frame acquired prior to contact in each trial, corresponding to a stable unloaded state of the elastomer. Before each trial, the sensor is reset to a no-contact condition and a new reference frame is captured under identical imaging and lighting conditions.

This study focuses on the effect of marker design on deformation information encoding, where preserving marker integrity is essential for the faithful transmission of deformation information. Accordingly, experiments are conducted under moderate deformation conditions to maintain marker integrity and avoid large deformation regimes, such as sliding and rotation, which may introduce material damage and confound the analysis.

Within the deformation regime considered, no visible surface damage or material degradation is observed across repeated trials. The material therefore exhibits repeatable elastic recovery, allowing the reference configuration to be consistently re-established at the start of each trial. Any residual hysteresis or drift is negligible compared with the deformation induced by applied forces and is further mitigated by trial-wise reference normalisation.

In cases where the elastomer is replaced, consistency is preserved by acquiring a new reference frame under identical imaging conditions, ensuring that all measurements are defined relative to their corresponding baseline configuration.

Together, these design choices ensure that the constructed dataset is both spatially and temporally consistent, providing a well-defined and physically grounded representation for analysing deformation-to-force relationships.

Regression model for normal force estimation

To estimate the applied normal force (F_z) from marker features, we trained a convolutional neural network (CNN) in a supervised regression setup. Input features were derived from time-synchronised marker data with force columns removed. We conducted 10 independent training runs to assess robustness and report performance statistics.

All features were standardised to zero mean and unit variance. The dataset was split into 80% training and 20% testing; within the training set, 20% was held out for validation. Feature matrices were reshaped to $(N, T, 1)$, where N denotes the number of markers, T denotes the temporal window length measured in frames, and the final dimension represents a single input channel.

To ensure a fair comparison across marker shapes, a single CNN architecture and identical training protocol were used for all experiments. The network comprised two convolutional layers (64 and 32 filters) each followed by max-pooling, then a flatten layer and two fully connected layers (32 units, ReLU activations), and a linear output neuron for (F_z) . Models were trained with Adam (learning rate (10^{-3})), mean squared error loss, batch size 32, for 100 epochs in TensorFlow using a fixed random seed (42).

Performance on the held-out test set was quantified using root mean square error (RMSE) and coefficient of determination (R^2), reported as mean $\pm$ s.d. across 10 runs. This section describes the primary CNN-based regression model.

Regression model for shear force estimation

To estimate the applied shear force (F_x or F_y) from marker features, we employed a Support Vector Regression (SVR) model in a supervised regression framework. Input features were extracted from time-synchronised marker datasets, with all force-related columns removed prior to training. Multiple datasets corresponding to different experimental trials were evaluated independently using an identical modelling pipeline. For each dataset, we conducted 10 independent training runs to assess robustness and report performance statistics.

Marker features were standardised to zero mean and unit variance using a z-score normalisation. The dataset was randomly split into 80% training and 20% testing sets for each run, with the random seed incremented across runs to ensure statistically independent splits while maintaining reproducibility. Unlike the CNN-based normal-force estimation, no temporal reshaping was applied, and features were treated as fixed-length vectors reflecting instantaneous marker displacement and area-change information.

SVR models were trained using a radial basis function (RBF) kernel, which provides sufficient nonlinearity to capture the relationship between marker motion and shear force while remaining computationally lightweight. The regularisation and kernel parameters were fixed across all experiments to ensure a fair comparison between marker configurations, with $C = 10.0$, $\epsilon = 0.01$, and γ set to the default scale heuristic. Target shear-force values were standardised during training and inverse-transformed after inference to recover predictions in physical units.

Model performance on the held-out test set was quantified using root mean square error (RMSE) and coefficient of determination (R^2), reported as mean $\pm$ s.d. across 10 runs. In addition, per-frame inference time was measured by repeatedly evaluating the trained SVR model on test samples after a warm-up phase, providing an estimate of computational cost relevant to real-time deployment. This SVR-based regression model serves as the primary estimator for shear force throughout the shear-dominated experiments; all marker configurations were evaluated using the same preprocessing, hyperparameters, and evaluation protocol. This section describes the primary SVR-based regression model.

Offset experiment design

To examine the effect of spatial variation in contact location on deformation-information encoding, we conducted controlled indentation experiments at multiple predefined positions across the sensing surface. The central contact condition is defined as the reference (offset = 0), while additional datasets were collected under identical normal loading conditions at selected offset locations.

Importantly, the chosen offset positions do not aim to exhaustively sample the entire spatial domain. Instead, they are defined relative to the central reference condition to provide a structured and controlled perturbation of contact location. This design enables a targeted investigation of

how spatial variation influences the fidelity of deformation representation, rather than evaluating generalisation across all possible contact positions.

All offset conditions were independently applied, rather than generated through lateral perturbation from a central contact, ensuring that the applied force remains consistent across all conditions while only the spatial location of contact is varied. The same CNN architecture was used for normal-force regression across datasets collected at different contact locations. In this experiment, RMSE is interpreted as a proxy for deformation-information fidelity under spatial perturbation. Variations in RMSE across offset conditions reflect how changes in contact position affect the consistency between the deformation patterns captured by the marker configuration and the corresponding force predictions.

Quantification of marker distribution

To systematically examine the influence of marker distribution on sensing performance, we designed a controlled factorial study along three orthogonal dimensions.

Marker density was defined as:

$$D = \frac{N}{A} \quad [\text{markers}/\text{mm}^2], \quad (4)$$

where N is the number of markers and A is the effective sensing area. Here, the effective sensing area refers to the projected area spanned by the marker matrix, rather than the entire elastomeric membrane. This definition ensures that density quantifies the number of markers available to sample deformation within the active region used for force estimation. Marker density directly reflects how finely the deformation field is sampled, thereby governing the trade-off between information content, computational cost, and tracking stability.

We further reported the fill factor:

$$\phi = \frac{N \cdot (\pi d^2 / 4)}{A}, \quad (5)$$

where d is the marker diameter, and the spacing p was defined as the centre-to-centre distance between adjacent markers. Unlike density, which primarily controls the sensing resolution, the fill factor represents the proportion of the surface covered by markers and mainly affects their optical visibility and tracking robustness.

Taken together, marker density and fill factor are two complementary descriptors of marker distribution. Among them, density is identified as the primary variable shaping performance trends, whereas fill factor plays a supporting role by ensuring that markers remain both detectable and non-overlapping during deformation.

Three experimental lines were implemented:

1. Sampling point effect (A-line): ϕ was held approximately constant by adjusting d in proportion to p , while varying N to isolate the effect of sampling resolution. Formally,

$$d \propto p, \quad \phi \approx \text{const.}, \quad N \uparrow. \quad (6)$$

2. Contrast effect (B-line): p was fixed while d was varied, thereby altering ϕ and the visibility of individual markers:

$$p = \text{const.}, \quad d \uparrow \Rightarrow \phi \uparrow. \quad (7)$$

3. Spatial bandwidth effect (C-line): d was fixed while p was changed, which simultaneously modified both D and ϕ :

$$d = \text{const.}, \quad p \downarrow \Rightarrow D \uparrow, \phi \uparrow. \quad (8)$$

We decomposed the effect of “distribution” into three underlying mechanisms.

A-line isolates sampling resolution by increasing the number of markers while keeping the overall marker coverage approximately constant; the global optical contrast is thus preserved and any accuracy gain is attributable to denser spatial sampling.

B-line fixes the spacing and varies the marker size, thereby changing the fill factor and visibility without altering the number of samples; this line captures the contrast contribution.

C-line fixes the marker size and changes the spacing, which jointly increases the number of samples and the fill factor; this line probes the effect of spatial bandwidth under constant local visibility.

To avoid optical overlap, a constraint was imposed:

$$p - d \geq \Delta_{\min}, \quad (9)$$

where $\Delta_{\min} \geq 2$ pixels denotes the minimum visible gap between adjacent markers in the captured image.

Performance evaluation metrics included force prediction accuracy:

$$\text{RMSE} = \sqrt{\frac{1}{M} \sum_{i=1}^M (\hat{F}_i - F_i)^2}, \quad (10)$$

$$R^2 = 1 - \frac{\sum_{i=1}^M (\hat{F}_i - F_i)^2}{\sum_{i=1}^M (F_i - \bar{F})^2}, \quad (11)$$

where F_i and $\hat{F}_i$ are the ground-truth and predicted forces, respectively, and M is the number of test samples.

To characterize the trade-off between accuracy and marker distribution, both density and fill factor were modeled with quadratic functions to capture the observed U-shaped performance trends. For marker density, the relationship was expressed as

$$\text{RMSE}(D) = aD^2 + bD + c, \quad D^* = -\frac{b}{2a}, \quad (12)$$

where D denotes marker density and D^* corresponds to the optimal sampling resolution. For fill factor, the relationship was similarly modeled as

$$\text{RMSE}(\phi) = \alpha\phi^2 + \beta\phi + \gamma, \quad \phi^* = -\frac{\beta}{2\alpha}, \quad (13)$$

where ϕ denotes the surface coverage ratio and ϕ^* the optimal coverage level.

Although density and fill factor are mathematically related through $\phi = D \cdot (\pi d^2/4)$, they emphasize different aspects of marker distribution: density governs the spatial sampling of deformation, whereas fill factor reflects optical coverage and marker visibility. In A-line, marker diameter was adjusted proportionally, making density the effective driver of performance. In B-line, however, density was held constant while marker diameter varied, so fill factor became the critical determinant of optical visibility and tracking robustness.

In C-line, since marker diameter was fixed, density and fill factor covaried linearly. The RMSE relationship can therefore be equivalently expressed in terms of either parameter:

$$\text{RMSE}(D) = aD^2 + bD + c \iff \text{RMSE}(\phi) = \alpha\phi^2 + \beta\phi + \gamma. \quad (14)$$

Both formulations describe the same U-shaped curve, and the optimal point is shared between D^* and ϕ^* . C-line therefore reflects the joint effect of increasing both sampling resolution and optical coverage.

Beyond accuracy alone, computational efficiency is a critical factor for real-time tactile sensing. We therefore introduced a cost function that jointly

accounts for error and inference speed, defined as

$$J = \text{RMSE} \times T_{\text{inf}}, \quad (15)$$

where T_{inf} denotes the average inference time per frame. Depending on the experimental line, J can be expressed as a function of density D (A- and C-lines) or fill factor ϕ (B-line). A lower value of J indicates a more favourable balance between predictive accuracy and computational efficiency.

Principal component and deformation stability analysis

To analyze the deformation behaviour of an $i \times i$ distributed marker matrix, we apply Principal Component Analysis (PCA) to displacement data under two configurations: displacement only and displacement combined with area change. These configurations provide complementary insights into the deformation characteristics of markers under applied forces.

PCA is a statistical technique that transforms high-dimensional data into a lower-dimensional space while preserving the most significant variance. The key steps involved in PCA for our $i \times i$ marker matrix are as follows:

For displacement-only data, each marker exhibits x - and y -displacement components, forming a feature vector as:

$$\mathbf{x}_t = [x_1^t, y_1^t, \dots, x_i^t, y_i^t]^\top \in \mathbb{R}^{2i^2} \quad (16)$$

where x_j^t and y_j^t denote the displacement of the j -th marker at time t .

For displacement and area change data, an additional feature a_j^t representing the area change of each marker is included:

$$\mathbf{x}_t = [x_1^t, y_1^t, a_1^t, \dots, x_i^t, y_i^t, a_i^t]^\top \in \mathbb{R}^{3i^2} \quad (17)$$

where x_j^t and y_j^t denote the x and y displacements, and a_j^t represents the area change of the j -th marker at time t .

The displacement dataset over m time steps is structured as:

$$\mathbf{X} = \begin{bmatrix} \mathbf{x}_1^\top \\ \mathbf{x}_2^\top \\ \vdots \\ \mathbf{x}_m^\top \end{bmatrix} \in \mathbb{R}^{m \times 2i^2} \quad (18)$$

where each row represents a single observation, and each column corresponds to a specific displacement feature.

During marker tracking, occasional missing displacement values occur, primarily at the boundaries of the deformation field where markers either move outside the field of view or become severely distorted. To maintain numerical stability, these missing values are replaced with the mean displacement of the corresponding feature:

$$X_{ij} = \begin{cases} X_{ij}, & \text{if } X_{ij} \neq \text{NaN} \\ \frac{1}{m} \sum_{t=1}^m X_{ij}, & \text{if } X_{ij} = \text{NaN} \end{cases} \quad (19)$$

where X_{ij} represents the displacement value of the j -th marker at time t .

To prevent numerical issues, features with zero variance are removed:

$$\sigma_j^2 = \frac{1}{m} \sum_{t=1}^m (X_{ij} - \bar{X}_j)^2 \quad (20)$$

where $\bar{X}_j$ is the mean displacement of the j -th feature.

To eliminate bias due to absolute displacement magnitudes, the mean displacement is subtracted from each feature:

$$\mathbf{X}_{\text{norm}} = \mathbf{X} - \bar{\mathbf{X}}, \quad \text{where } \bar{\mathbf{X}} = \frac{1}{m} \sum_{t=1}^m \mathbf{x}_t \quad (21)$$

This ensures that PCA captures variance rather than absolute values.

The covariance matrix captures how marker displacements are inter-related:

$$\mathbf{C} = \frac{1}{m-1} \mathbf{X}_{\text{norm}}^{\top} \mathbf{X}_{\text{norm}} \quad (22)$$

where C_{jk} measures the correlation between displacement components. Large C_{jk} values indicate strong correlations, while near-zero values suggest weak dependencies.

Eigenvalue decomposition is performed on $\mathbf{C}$:

$$\mathbf{C}\mathbf{V} = \mathbf{V}\mathbf{\Lambda} \quad (23)$$

where:

$\mathbf{\Lambda} = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_{2i^2})$ contains the eigenvalues (sorted in descending order).

$\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_{2i^2}]$ consists of eigenvectors (principal components).

Each principal component (PC) corresponds to a dominant deformation mode: PC1 (largest λ_1) captures the primary deformation direction. Higher-order PCs represent secondary deformation behaviours.

The transformed dataset in the principal component space is:

$$\mathbf{Z} = \mathbf{X}_{\text{norm}} \mathbf{V} \quad (24)$$

where $\mathbf{Z}$ represents displacement data in the reduced feature space.

To determine the number of components required, the explained variance ratio (EVR) is computed:

$$\text{EVR}_k = \frac{\lambda_k}{\sum_{j=1}^d \lambda_j}, \quad d = 2i^2 (\text{displacement - only}), 3i^2 (\text{displacement + area}) \quad (25)$$

The cumulative explained variance is:

$$\sum_{k=1}^K \text{EVR}_k \geq 95\% \quad (26)$$

where K is the minimum number of PCs needed to retain at least 95% of the variance.

Quantitative evaluation of deformation stability in concentric ring structures using Hu moments

Hu moments ($I_1, I_2, I_3, I_4, I_5, I_6, I_7$) are shape descriptors that exhibit invariance to translation, rotation, and scaling, making them powerful tools for quantifying geometric deformations. These moments capture key attributes such as symmetry, irregularity, and complexity, allowing for a robust assessment of marker deformation under applied forces.

Lower-order Hu Moments (I_1, I_2): Lower-order Hu moments, such as I_1 and I_2 , primarily describe fundamental shape properties, including size and symmetry. These moments are particularly insightful for analyzing highly symmetric shapes, such as circular markers, which tend to exhibit minimal variations under deformation, thereby ensuring stable force estimation.

Higher-order Hu Moments (I_3, I_4, I_5, I_6, I_7): Higher-order Hu moments provide a measure of shape complexity and asymmetry. Non-circular shapes, such as squares and triangles, display significant variations in these moments during deformation due to localised stress concentrations. As a result, higher-order Hu moments are essential for distinguishing different deformation patterns and assessing structural irregularities.

To systematically evaluate the stability of different concentric ring structures, we analyze the rate of change of Hu moments across deformation

stages. A standardization process ensures comparability across moment features.

For each Hu moment feature H_i , standardization is performed to eliminate scale differences across different deformation stages:

$$\hat{H}_{ij}(t_k) = \frac{H_{ij}(t_k) - \mu_{ij}}{\sigma_{ij}}, \quad i = 1, \dots, 7 \quad (27)$$

where:

$\hat{H}_{ij}(t_k)$ is the standardized i -th Hu moment for the j -th ring at deformation stage t_k , $H_{ij}(t_k)$ is the original Hu moment value, μ_{ij} and σ_{ij} are the mean and standard deviation of the moment feature across all deformation stages.

This normalization ensures that all features contribute equally to the analysis.

The instantaneous change in Hu moments between adjacent deformation stages is computed as:

$$\Delta \hat{H}_{ij}(t_k) = \left| \hat{H}_{ij}(t_{k+1}) - \hat{H}_{ij}(t_k) \right| \quad (28)$$

To obtain a single measure of deformation stability, we compute the average rate of change across all seven Hu moment features:

$$\Delta \hat{H}_{\text{mean},j}(t_k) = \frac{1}{7} \sum_{i=1}^7 \Delta \hat{H}_{ij}(t_k) \quad (29)$$

A lower value of $\Delta \hat{H}_{\text{mean},j}(t_k)$ indicates higher deformation stability.

For each ring, the average rate of change across all deformation stages is computed as:

$$\Delta \hat{H}_{\text{ring mean},j} = \frac{1}{n-1} \sum_{k=1}^{n-1} \Delta \hat{H}_{\text{mean},j}(t_k) \quad (30)$$

where n is the total number of deformation stages.

The final dataset-wide metric for deformation stability is obtained by averaging across all ring configurations:

$$\Delta \hat{H}_{\text{dataset mean}} = \frac{1}{J} \sum_{j=1}^J \Delta \hat{H}_{\text{ring mean},j} \quad (31)$$

where J represents the number of different ring configurations under evaluation.

This metric provides an aggregate measure of deformation irregularity across all tested configurations, where lower values indicate higher stability.

Geometric fitting analysis using residual sum of squares

To evaluate how well different marker geometries align with observed deformation patterns, we employed a geometric fitting method based on the residual sum of squares (RSS). This metric quantifies the deviation between experimental marker positions and idealised geometric templates (circles, hexagons, pentagons). By comparing RSS values, we determined which geometry provides the closest alignment to the deformation field, thereby informing marker optimisation.

Each ring within the structured marker configuration follows a defined radial spacing. The radius r_i of the i -th ring is given by

$$r_i = i \times \text{radius_interval}, \quad i = 1, 2, \dots, N_{\text{rings}}, \quad (32)$$

where N_{rings} denotes the total number of concentric rings.

The distance of each marker from the expected boundary varies based on the geometric structure being evaluated. We provide formulations for circular, pentagonal, and hexagonal markers.

For a regular n -sided polygon, the distance of a marker located at (x_j, y_j) from the nearest edge is computed as:

$$d_{\text{polygon}}(x_j, y_j) = r_i \cdot \frac{\cos(\pi/n)}{\cos((\theta_j \bmod (2\pi/n)) - \pi/n)}, \quad (33)$$

where θ_j is the angular position of the marker relative to the polygon center:

$$\theta_j = \arctan 2(y_j - y_0, x_j - x_0). \quad (34)$$

Here, r_i represents the radius of the ring, n denotes the number of polygon sides ($n = 5$ for pentagons and $n = 6$ for hexagons), and the modulus operation ensures that the angle remains within a single polygonal segment.

For circular markers, the expected distance from the center remains constant:

$$d_{\text{circle}}(x_j, y_j) = r_i. \quad (35)$$

This assumption holds for uniformly spaced concentric ring markers.

For each ring, the residual sum of squares (RSS) quantifies the fitting error by summing the squared deviations of the observed marker distances from their respective expected distances:

$$RSS_i = \sum_{j=1}^N \left((d_j - d_{\text{fit},j})^2 \cdot w_j \right), \quad (36)$$

where d_j is the observed distance of marker j , $d_{\text{fit},j}$ is the expected distance based on the geometric fit, and w_j is a weighting factor that accounts for marker importance.

To evaluate the overall geometric fitting accuracy, we compute the mean RSS across all rings:

$$RSS_{\text{mean}} = \frac{1}{N_{\text{rings}}} \sum_{i=1}^{N_{\text{rings}}} RSS_i. \quad (37)$$

A lower RSS_{mean} value indicates a better geometric fit, implying that the chosen shape effectively represents marker deformation patterns.

Data availability

The datasets generated and/or analyzed during the current study are not publicly available due to ongoing related research projects, but are available from the corresponding author on reasonable request. The code used in this study is also available from the corresponding author on reasonable request.

Received: 1 October 2025; Accepted: 27 August 2026;

Published online: 14 September 2026

References

- Park, H. & Cha, Y. Liquid classification in robotic fingers with multimodal tactile sensor system. *npj Robot.* **3**, 33 (2025).
- Junge, K. & Hughes, J. Adapt-teleop: robotic hand with human matched embodiment enables dexterous teleoperated manipulation. *npj Robot.* **3**, 31 (2025).
- Fang, B. et al. Force measurement technology of vision-based tactile sensor. *Adv. Intell. Syst.* **7**, 2400290 (2025).
- Yuan, W., Dong, S. & Adelson, E. H. Gelsight: High-resolution robot tactile sensors for estimating geometry and force. *Sensors* **17**, 2762 (2017).
- Zhang, L., Feng, S., Li, T. & Jiang, Y. Evaluation, selection and validation of force reconstruction models for vision-based tactile sensors. *Measurement* **226**, 114188 (2024).
- Wang, Z. et al. Tactile perception: a biomimetic whisker-based method for clinical gastrointestinal diseases screening. *npj Robot.* **1**, 3 (2023).
- Lambeta, M. et al. Digit: a novel design for a low-cost compact high-resolution tactile sensor with application to in-hand manipulation. *IEEE Robot. Autom. Lett.* **5**, 3838–3845 (2020).
- Tashakori, A. et al. Capturing complex hand movements and object interactions using machine learning-powered stretchable smart textile gloves. *Nat. Mach. Intell.* **6**, 106–118 (2024).
- Baimukashev, D., Kappasov, Z. & Varol, H. A. Shear, torsion and pressure tactile sensor via plastic optofiber guided imaging. *IEEE Robot. Autom. Lett.* **5**, 2618–2625 (2020).
- He, L., Lu, Q., Abad, S.-A., Rojas, N. & Nanayakkara, T. Soft fingertips with tactile sensing and active deformation for robust grasping of delicate objects. *IEEE Robot. Autom. Lett.* **5**, 2714–2721 (2020).
- Li, W. et al. F-touch sensor: concurrent geometry perception and multi-axis force measurement. *IEEE Sens. J.* **21**, 4300–4309 (2020).
- Bandari, N., Dargahi, J. & Packirisamy, M. Tactile sensors for minimally invasive surgery: a review of the state-of-the-art, applications, and perspectives. *IEEE Access* **8**, 7682–7708 (2019).
- Lin, X. & Wiertelowski, M. Sensing the frictional state of a robotic skin via subtractive color mixing. *IEEE Robot. Autom. Lett.* **4**, 2386–2392 (2019).
- Yan, Y., Zermane, A., Pan, J. & Kheddar, A. A soft skin with self-decoupled three-axis force-sensing taxels. *Nat. Mach. Intell.* **6**, 1284–1295 (2024).
- Lin, C., Zhang, H., Xu, J., Wu, L. & Xu, H. 9dtact: a compact vision-based tactile sensor for accurate 3d shape reconstruction and generalizable 6d force estimation. *IEEE Robot. Autom. Lett.* **9**, 923–930 (2023).
- Sferrazza, C. & D'Andrea, R. Design, motivation and evaluation of a full-resolution optical tactile sensor. *Sensors* **19**, 928 (2019).
- Sun, H., Kuchenbecker, K. J. & Martius, G. A soft thumb-sized vision-based sensor with accurate all-round force perception. *Nat. Mach. Intell.* **4**, 135–145 (2022).
- Yuan, W., Li, R., Srinivasan, M. A. & Adelson, E. H. Measurement of shear and slip with a gelsight tactile sensor. In *2015 IEEE International Conference on Robotics and Automation (ICRA)*, 304–311 (IEEE, 2015).
- Xu, J., Chen, W., Qian, H., Wu, D. & Chen, R. Thintact: Thin vision-based tactile sensor by lensless imaging. *IEEE Transactions on Robotics* (2025).
- Ko, D.-K., Lee, K.-W., Lee, D. H. & Lim, S.-C. Vision-based interaction force estimation for robot grip motion without tactile/force sensor. *Expert Syst. Appl.* **211**, 118441 (2023).
- Ou, N., Chen, Z. & Luo, S. Marker or markerless? Mode-switchable optical tactile sensing for diverse robot tasks. *IEEE Robotics Automation Lett.* **9**, 8563–8570 (2024).
- Tijani, O., Chen, Z., Deng, J. & Luo, S. MagicSkin: Balancing marker and markerless modes in vision-based tactile sensors with a translucent skin. *arXiv preprint arXiv:2512.06829* (2025).
- Luo, S. et al. Tactile robotics: An outlook. *IEEE Transactions on Robotics* (2025).
- Jiang, C. et al. Capturing forceful interaction with deformable objects using a deep learning-powered stretchable tactile array. *Nat. Commun.* **15**, 9513 (2024).
- Lu, Z. et al. 3d force identification and prediction using deep learning based on a gelsight-structured sensor. *Sens. Actuators A: Phys.* **367**, 115036 (2024).
- Masui, K. et al. Vision-based estimation of manipulation forces by deep learning of laparoscopic surgical images obtained in a porcine excised kidney experiment. *Sci. Rep.* **14**, 9686 (2024).
- He, L., Herzig, N., Nanayakkara, T. & Maiolino, P. 3D-printed soft sensors for adaptive sensing with online and offline tunable stiffness. *Soft Robot.* **9**, 1062–1073 (2022).

28. Sui, M. et al. A soft-packaged and portable rehabilitation glove capable of closed-loop fine motor skills. *Nat. Mach. Intell.* **5**, 1149–1160 (2023).
29. Zhang, G., Du, Y., Yu, H. & Wang, M. Y. Deltact: A vision-based tactile sensor using a dense color pattern. *IEEE Robot. Autom. Lett.* **7**, 10778–10785 (2022).
30. Donlon, E. et al. Gelslim: A high-resolution, compact, robust, and calibrated tactile-sensing finger. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 1927–1934 (IEEE, 2018).
31. Mao, Q., Liao, Z., Yuan, J. & Zhu, R. Multimodal tactile sensing fused with vision for dexterous robotic housekeeping. *Nat. Commun.* **15**, 6871 (2024).
32. Mirzaee, M. A., Huang, H.-J. & Yuan, W. Gelbelt: A vision-based tactile sensor for continuous sensing of large surfaces. *IEEE Robotics Automation Lett.* **10**, 2016–2023 (2025).
33. Tang, T. et al. A shape memory alloy spring driven soft crawling robot with feet of constant curvature. *J. Intell. Mater. Syst. Struct.* **34**, 2393–2403 (2023).
34. Shorthose, O., Albin, A., He, L. & Maiolino, P. Design of a 3d-printed soft robotic hand with integrated distributed tactile sensing. *IEEE Robot. Autom. Lett.* **7**, 3945–3952 (2022).
35. Zenha, R., Denoun, B., Cavallaro, A., Bernardino, A. & Jamone, L. Let's dense: a novel protocol for efficiently collecting dense and diverse data for tactile slip detection in robotic grasping. *npj Robot.* **3**, 36 (2025).
36. Ma, D., Donlon, E., Dong, S. & Rodriguez, A. Dense tactile force estimation using gelslim and inverse fem. In *2019 International Conference on Robotics and Automation (ICRA)*, 5418–5424 (IEEE, 2019).
37. Nanayakkara, T. (ed.) *Handbook on Soft Robotics* (Springer Nature, UK London, 2024).
38. Yao, K. et al. Encoding of tactile information in hand via skin-integrated wireless haptic interface. *Nat. Mach. Intell.* **4**, 893–903 (2022).
39. Li, M., Zhang, L., Li, T. & Jiang, Y. Continuous marker patterns for representing contact information in vision-based tactile sensor: Principle, algorithm, and verification. *IEEE Trans. Instrum. Meas.* **71**, 1–12 (2022).
40. Li, M., Zhou, Y. H., Li, T. & Jiang, Y. Improving the representation and extraction of contact information in vision-based tactile sensors using continuous marker pattern. *IEEE Robot. Autom. Lett.* **8**, 6021–6028 (2023).
41. Ma, H. & Ji, J. Full-array markers tracking adapted to large contact distortion in visuotactile sensing. *IEEE Sens. J.* **24**, 14018–14026 (2024).
42. Yergibay, M. et al. Nusense: Robust soft optical tactile sensor. *arXiv preprint arXiv:2410.23516* (2024).
43. Abad, A. C. & Ranasinghe, A. Low-cost gelsight with UV markings: Feature extraction of objects using alexnet and optical flow without 3d image reconstruction. In *2020 IEEE international conference on robotics and automation (ICRA)*, 3680–3685 (IEEE, 2020).
44. Kim, W., Kim, W. D., Kim, J.-J., Kim, C.-H. & Kim, J. Uvtac: Switchable uv marker-based tactile sensing finger for effective force estimation and object localization. *IEEE Robot. Autom. Lett.* **7**, 6036–6043 (2022).
45. Li, W. et al. L3 f-touch: a wireless gelsight with decoupled tactile and three-axis force sensing. *IEEE Robot. Autom. Lett.* **8**, 5148–5155 (2023).

Acknowledgements

The authors acknowledge the funding support from the ARIA grant (SMRB-SE01-P03) and the EU Horizon 2020 research and innovation programme (No. 101016970). T.T. thanks Prof. Etienne Burdet (Imperial College London), Prof. Perla Maiolino (University of Oxford), and Prof. Robert Baines (ETH Zurich) for helpful discussions and guidance during lab visits. T.T. also acknowledges Amazon for the Amazon Robotics Prize recognition received in both 2025 and 2026, as part of a collaborative initiative between Imperial College London and Amazon to recognise outstanding contributions in robotics research.

Author contributions

T.T. conceived the core idea and proposed the Marker Information Efficacy (MIE) framework, designed and fabricated the sensor, conducted the experiments, and performed the data analysis. T.T. drafted and revised the manuscript. T.N. supervised the research, provided conceptual guidance, and reviewed and edited the manuscript. Both authors discussed the results and approved the final version of the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1038/s44182-026-00115-x>.

Correspondence and requests for materials should be addressed to Tonghui Tang or Thrishantha Nanayakkara.

Reprints and permissions information is available at <http://www.nature.com/reprints>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

© The Author(s) 2026