Classifying liquids with LiDAR

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ABSTRACT

The ability to classify liquids based on their physical properties is crucial in various industrial and scientific applications. This paper presents a novel approach to liquid classification using LiDAR technology, focusing on the correlation between speckle intensity fluctuations and Brownian motion to identify differences in viscosity. By capturing time-series LiDAR data, we analyze the speckle patterns generated on the surface of different liquids and study their correlation with underlying motion. Brownian motion, which varies with viscosity, is used as a key parameter to distinguish liquids. The experiment uses non-transparent, easily available liquids with comparable viscosity to refine the classification process. The purpose of this is to identify any potential adulteration in the liquids by identifying the deviation between the expected viscosity of a liquid and observed viscosity using this device.The proposed method effectively identifies liquids based on their viscosity, demonstrating a promising step towards non-contact and efficient liquid classification.

KEYWORDS

Viscosity, BrownianMotion, Liquids, Dairy products, Conferences, LiDAR, Speckle Pattern, Liquid Analysis

1 INTRODUCTION

The application of LiDAR for classifying liquids has gained traction due to its ability to perform contactless fluid analysis by capturing laser speckle patterns. When coherent laser light is directed at a liquid, light scattered by particles within it forms a speckle pattern [2] whose fluctuations reflect key properties like viscosity. This phenomenon, known as laser speckle reflectometry, reveals differences in viscosity based on the rate of Brownian motion [4] within the liquid, which is affected by particle size and density. As such, higher-viscosity liquids tend to exhibit more stable speckle patterns, while lower-viscosity liquids produce patterns with more rapid fluctuations.

Recent advancements have leveraged smartphone LiDAR technology for speckle pattern analysis, expanding the accessibility of liquid classification techniques. Smartphone-based LiDAR systems capture high-resolution speckle patterns and analyze their temporal dynamics, enabling researchers to distinguish between liquid types based on subtle differences in particle movement and viscosity. Studies have shown that these systems can classify a variety of liquids by identifying unique speckle "signatures" for each liquid. For instance, a smartphone LiDAR setup demonstrated effectiveness in differentiating milk by fat content, detecting adulterants, and even identifying coagulation states in blood samples, as highlighted in research from the University of Washington [1].

This study builds on the theoretical foundations of laser speckle theory and its relationship with Brownian motion to classify non-transparent liquids based on viscosity. By leveraging advancements in LiDAR technology, this work contributes to ongoing research on contactless, efficient liquid analysis and demonstrates the potential for rapid, portable fluid classification in practical settings.

2 RELATED WORKS

Recent advancements in smartphone LiDAR technology have opened up new avenues for non-invasive liquid sensing, enabling applications that range from food safety to medical diagnostics. Hota, Saha, and Chakraborty (2024) [3] pioneered an approach called LiSTA, which uses smartphone LiDAR to analyze time-varying properties such as viscosity. LiSTA stands out because it requires only a single drop of liquid and can be performed without laboratory equipment, making it accessible for everyday use. Their study demonstrates its versatility across applications, including detecting baby food spoilage, estimating calorie content in drinks, and identifying milk adulteration, highlighting its potential for pervasive, real-world liquid analysis.

Chan et al. (2022)[1] explored smartphone LiDAR for liquid testing at a microscopic level. Their approach focuses on analyzing speckle patterns produced by the LiDAR dots when they interact with liquids, capturing physical properties like turbidity and refractive index. This method showed promise in identifying liquids with subtle differences, making it suitable for applications where quick and accessible testing is required, such as in clinical or food safety contexts.

Foundational research on speckle pattern analysis provides the basis for these liquid sensing methods. Dong and Pan (2017) [2] reviewed speckle pattern fabrication and evaluation techniques for digital image correlation (DIC), an approach traditionally used in strain and deformation analysis. Their review outlines how precise speckle patterns can be generated and assessed, forming a crucial component for image-based techniques like those used in LiDAR-based liquid classification. By building on these speckle analysis techniques, researchers have adapted them to work with smartphone LiDAR, enhancing their applicability for non-contact liquid characterization.

(a) Experimental setup **(b) Experimental Setup**

Figure 1: Images showing different angles of the Experimental Setup

Together, these studies underscore the potential of smartphone-based LiDAR and speckle analysis to transform liquid sensing. By integrating LiDAR's non-contact capabilities with speckle pattern analysis, researchers have devised accessible, portable methods for real-time liquid classification. This convergence of technologies demonstrates how smartphones can be effectively used beyond spatial mapping, establishing their role in practical, everyday liquid testing applications across various fields.

3 EXPERIMENTAL SETUP

The experimental setup for classifying liquids using LiDAR comprises a smartphone-based LiDAR sensor, a Raspberry Pi for data acquisition and processing, and a custom-built liquid holder with proper alignment for laser projection and speckle capture.

(1) **Smartphone with LiDAR Projection:**: The iPhone is used to project LiDAR dots onto the surface of the liquid sample. The smartphone camera app is opened solely to activate the LiDAR sensor, projecting a grid of dots that interact with the liquid. This interaction produces speckle patterns, which vary depending on the properties of the liquid, particularly viscosity. The smartphone itself is not used for data capture; it only functions as a source for LiDAR dot projection.
(2) **Raspberry Pi and Camera Interface**: The Raspberry Pi is placed adjacent to the smartphone and acts as the main processing unit. It is equipped with a camera interface module connected via a ribbon cable. The camera connected to the Raspberry Pi captures images of the laser speckle pattern in real time, processing and storing the data for later analysis. This modular setup allows for easy adjustments and ensures that data collection can be automated with minimal intervention.
(3) **Wooden and glass slab for liquid**: A drop of the liquid is placed carefully on the glass slab and that glass slab is carefully positioned directly below the camera setup on the wooden slab, which holds the liquid sample in place. The wooden slab ensure minimal movement of the liquid, thus reducing noise in the speckle patterns caused by external vibrations. The LiDAR dots from the iPhone is projected onto the liquid through an opening in the holder, generating a speckle pattern that is recorded by the camera connected to the Raspberry Pi.
(4) **Structural Stability**: The entire assembly is supported using boxes and other materials to maintain a fixed distance and angle between the laser, liquid sample, and camera. This structural support ensures consistent capture of speckle patterns across all samples, making the measurements more reliable and repeatable.

This setup enables easy recording of videos of liquids and analyzing speckle patterns generated by the LiDAR. The design also provides flexibility for adjustments in positioning, enabling precise alignment and repeatable experimentation in different liquid samples.

4 DATA COLLECTION

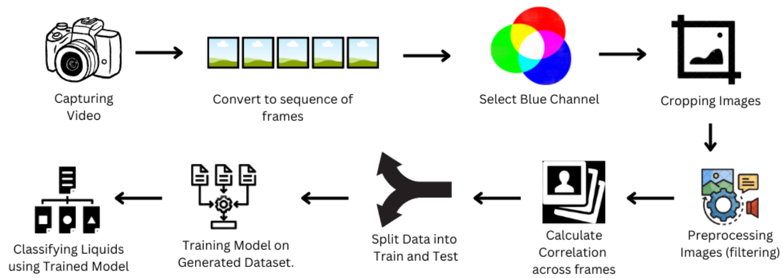
4.1 Equipment and Setup

We utilized an **iPhone 15 Pro Max** for its LiDAR sensor capabilities, alongside a **Raspberry Pi NoIR Camera V2** (without an infrared filter) to capture time-varying speckle patterns generated by liquid samples. This setup enabled us to analyze the Brownian motion of particles in the liquid samples and their correlation with viscosity changes.

4.2 Experimental Conditions

To maintain consistent environmental conditions across all tests, each liquid sample was measured at **room temperature** and in a controlled **relative humidity** environment. Given that temperature and humidity can significantly influence viscosity, these conditions were essential for obtaining reliable and reproducible data.

- **Liquid Volume**: Experiments were conducted with minimal liquid quantities, specifically between **10 μL to 50 μL**.
- **Camera Settings**: The camera's shutter speed was set to **1/30 s** with a **2x zoom** applied.



(a) Methodology

(b) Data Recording of Milk

Figure 2: (a). Workflow for Classifying Liquids Using LiDAR Data (b). Figure shows the LiDAR dots projected on drop of liquid of Milk for data reading.

- **Distance and Surface**: A fixed distance of **8 cm** was maintained between the LiDAR-equipped iPhone and the liquid droplet. Non-reflective surfaces and minimal background light further reduced potential interference in speckle pattern generation.

4.3 Materials and Sample Selection

Each liquid sample was carefully placed on a stationary glass slide, as any movement could disrupt the speckle pattern generated by the LiDAR, compromising measurement accuracy.

Our selection criteria focused on commonly used **opaque liquids**, as transparent liquids were unsuitable for our technique due to the need for consistent speckle patterns. We chose the following five readily available liquids with varying viscosities to assess the effectiveness of our classification model:

- Milk
- Mango Juice
- Tomato Sauce
- Kesar Pista Ice Cream
- Butterscotch Ice Cream

These selections allow us to explore a range of viscosities and textures, which could simulate potential adulterants or inconsistencies in common products. By analyzing LiDAR-based speckle intensity fluctuations in these samples, we aim to establish a clear correlation with viscosity, serving as a basis for classifying and detecting adulterants in liquids.

4.4 Laser-Speckle Pattern Analysis

The iPhone LiDAR emits **near-infrared laser pulses in a 24×24 grid pattern**. When these laser pulses are directed at a liquid droplet, light scattering occurs due to particles suspended within the liquid, leading to the formation of speckle patterns. These patterns vary depending on whether the laser is pointed at a liquid or solid surface:

- **Solid Surface**: Speckle patterns are generally stable, as they correlate with the roughness of the surface, known as an *objective speckle* pattern.
- **Liquid Surface**: In contrast, laser interaction with a liquid creates dynamic speckle patterns due to the Brownian motion of particles, such as RBCs or WBCs in blood samples. This time-dependent variation in speckle patterns is fundamental for classifying liquids, as it reflects their viscosity characteristics.

This approach enables us to detect deviations in viscosity from expected values, which can help in identifying potential adulterants. By using speckle intensity fluctuations, we aim to establish a reliable, non-contact method for liquid classification and adulteration detection.

5 METHODOLOGY

Our methodology for liquid classification using LiDAR technology follows a systematic workflow comprising seven main stages Fig.2a.

5.1 Video Capture

The process begins with video data acquisition using the following setup:

- iPhone 15 Pro Max LiDAR projecting a 24×24 grid pattern of near-infrared laser pulses
- Liquid samples (10-50 μL) positioned on a glass slide at 8 cm from LiDAR
- Raspberry Pi NoIR Camera V2 recording at 30 fps
- Environmental controls:
  - Room temperature conditions.
  - Controlled humidity.
  - Non-reflective surface.
  - Minimal background lighting.
  - Camera settings: 1/30s shutter speed, 2x zoom.

5.2 Frame Sequence Generation

The captured video is processed to extract frame sequences:

- 30-second video recordings converted to individual frames.
- First and last 2 seconds removed to eliminate transitional movements.
- Frame extraction at 30 fps rate for optimal pattern analysis.
- Storage of frames in sequential order for subsequent processing.

5.3 Blue Channel Selection

Color channel processing is performed to optimize speckle pattern analysis:

- Extraction of blue channel from RGB frames.
- Enhanced visibility of speckle patterns.
- Storage of blue channel data for feature extraction.

5.4 Image Cropping

Region of Interest (ROI) selection through dynamic cropping:

- Square region covering the entire liquid drop identified
- Final ROI cropping for all selected frames

5.5 Image Preprocessing

Enhancement and filtering of cropped images:

- Removal of static speckle patterns.
- Applied threshold 80 to filter only usable images.
- Filtering of frames affected by LiDAR flickering.

5.6 Correlation Analysis

Frame-to-frame correlation computation:

- Two-dimensional correlation analysis between consecutive frames
- Correlation coefficient (C) calculation using the formula:

$$C = \frac{\sum_{x=0}^{X} \sum_{y=0}^{Y} (I_{xy}(t) - \bar{I}(t))(I_{xy}(t+\tau) - \bar{I}(t+\tau))}{\sqrt{(\sum_{x,y}(I_{xy}(t) - \bar{I}(t))^2)(\sum_{x,y}(I_{xy}(t+\tau) - \bar{I}(t+\tau))^2)}} \quad (1)$$

  where $\bar{I}(t)$ represents average intensity at time t
- Generation of correlation curves for viscosity assessment
- Calculation of normalized viscosity coefficient (V)

5.7 Dataset Generation and Model Training

Creation and processing of training dataset:

- Collection of processed images from various liquid samples:
  - Milk
  - Mango Juice
  - Tomato Sauce
  - Kesar Pista Ice Cream
  - Butterscotch Ice Cream
- Dataset split into training and testing sets
- Feature extraction from speckle patterns:
  - Intensity fluctuations
  - Pattern correlations
  - Temporal variations
- Model training on generated dataset

5.8 Liquid Classification

Final classification implementation:

- Application of the trained model to new liquid samples
- Classification based on speckle pattern characteristics
- Generation of classification metrics:
  - Accuracy
  - Precision
  - Recall
  - F1-score
- Validation against known liquid properties

The methodology integrates hardware configuration, image processing, and machine learning techniques to create a robust system for liquid classification using LiDAR-generated speckle patterns. Each stage is designed to maintain consistency and reproducibility while ensuring accurate liquid classification based on viscosity characteristics.

6 EXPERIMENTS

We evaluated our LiDAR-based liquid classification system using two distinct datasets and conducted comprehensive performance analysis using various metrics. The evaluation was performed using a Random Forest classifier with a 70-15-15 split for training, validation, and testing respectively.

6.1 Dataset Organization

We organized our experiments around two different datasets:

6.1.1 Four-Liquid Dataset. The first dataset comprised four different liquids:

- Kesar Pista Ice Cream.
- Mango Juice.
- Milk.
- Tomato Sauce.

6.1.2 Two-Liquid Dataset. The second dataset focused on distinguishing between two types of ice cream:

- Kesar Pista Ice Cream.
- Butterscotch Ice Cream.

6.2 Performance Analysis

6.2.1 Four-Liquid Classification Results. For the four-liquid classification task, our model demonstrated strong performance across all metrics [Table 1]:

Table 1: Test Results for Four-Liquid Classification

Liquid	Precision	Recall	F1-Score	Support
Kesar Pista	0.87	0.93	0.90	14
Mango	0.96	0.96	0.96	25
Milk	1.00	0.95	0.98	21
Sauce	1.00	1.00	1.00	12
Accuracy		0.96		72
Macro Avg	0.96	0.96	0.96	72
Weighted Avg	0.96	0.96	0.96	72

The validation results showed:

- Overall accuracy: 80.56%.
- Particularly strong performance in milk classification (precision = 1.00, recall = 1.00).
- Consistent performance across different liquid types.

6.2.2 Two-Liquid Sub-Classification Results. For the binary classification between ice cream types [Table 2]:

The validation results demonstrated:

- Overall accuracy: 91.67%.

Table 2: Test Results for Two-Liquid Sub-Classification

Ice Cream Type	Precision	Recall	F1-Score	Support
Butterscotch	0.80	0.92	0.86	13
Kesar Pista	0.95	0.87	0.91	23
Accuracy		0.89		36
Macro Avg	0.88	0.90	0.88	36
Weighted Avg	0.90	0.89	0.89	36

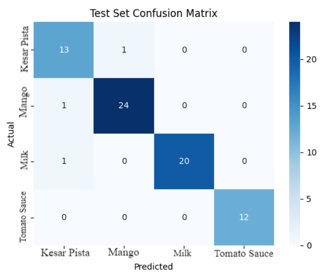


Figure 3: 4 Liquid Classification Confusion Matrix

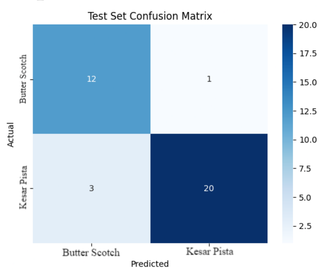


Figure 4: 2 Liquid Sub-Classification Confusion Matrix

- Strong performance in distinguishing between ice cream types.
- Balanced precision and recall scores.

6.3 Confusion Matrix Analysis

The confusion matrices reveal several important insights:

6.3.1 Four-Liquid Classification [Figure 3].

- High accuracy in identifying sauce (100% correct classifications).
- Minor confusion between similar liquids (e.g., 1 misclassification between categories).
- Strong diagonal dominance indicating reliable classification.

6.3.2 Two-Liquid Sub-Classification [Figure 4].

- Only 4 total misclassifications out of 36 samples.
- Better performance in identifying Kesar Pista (20 correct out of 23).
- Minimal false positives between categories.

6.4 Key Findings

Our evaluation demonstrates several significant results:

- The system achieves high accuracy in both multi-class (96%) and Sub-Classification of Different flavours of Ice Cream (89%) classification tasks.
- Robust performance across different liquid types, especially with distinguishing features.
- Consistent performance between validation and test sets, indicating good generalization.
- Higher accuracy in distinguishing between more distinct liquids (e.g., milk vs. sauce) compared to similar ones (e.g., different ice cream types).

These results validate the effectiveness of our LiDAR-based approach for liquid classification, showing particular strength in distinguishing between liquids with different viscosity characteristics.

7 CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

This research presents a novel approach to liquid classification using LiDAR technology, demonstrating the potential of speckle pattern analysis for non-invasive liquid identification. Our methodology achieves significant results with classification accuracies of 96% for multi-class liquid identification and 89% for binary classification between similar liquids. The system successfully distinguishes between various liquids based on their viscosity characteristics, as evidenced by the speckle patterns generated through LiDAR interaction.

Key achievements of our work include:

- Development of a robust preprocessing pipeline for LiDAR-generated speckle patterns.
- Successful implementation of correlation analysis for viscosity assessment.
- High accuracy in distinguishing between liquids with similar properties.
- Demonstration of liquid classification using commercially available iPhone LiDAR sensors, making the technology accessible without specialized equipment.
- Creation of a reproducible framework for non-contact liquid classification.

The system's ability to achieve high precision and recall scores across different liquid types demonstrates its potential for practical applications in quality control, food safety, and liquid authentication scenarios.

7.2 Future Scope

Based on our findings, several promising directions for future research emerge:

7.2.1 Application Extensions.

- Expansion of the liquid database to include a wider range of substances
- Development of mobile applications for easy deployment and use
- Integration with IoT systems for automated quality control
- Investigation of temporal changes in liquid properties over extended periods

7.2.2 Research Directions.

- Exploration of advanced deep learning architectures for pattern recognition
- Investigation of multi-modal sensing approaches combining LiDAR with other technologies
- Study of temperature and environmental effects on classification accuracy
- Analysis of micro-particle detection capabilities for contamination assessment

7.3 Potential Applications

The technology shows promise for various practical applications:

- Food and beverage industry quality control
- Pharmaceutical product verification
- Industrial liquid processing monitoring
- Consumer product authentication
- Adulteration detection in commercial products

Future work will focus on addressing current limitations and expanding the system's capabilities. Specific areas of improvement include:

- Development of more sophisticated preprocessing algorithms to handle varying environmental conditions
- Integration of temperature compensation mechanisms for more accurate viscosity assessment
- Investigation of multi-parameter analysis beyond viscosity
- Creation of standardized testing protocols for different liquid types
- Enhancement of the classification model to handle a broader range of liquid varieties

The promising results obtained in this study lay the groundwork for future advancements in non-contact liquid analysis using LiDAR technology. As smartphone LiDAR technology continues to evolve, we anticipate further improvements in accuracy and capabilities, making this approach increasingly viable for real-world applications.

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