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.

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

(a) Experimental setup

(b) Experimental Setup

Figure 1: Images showing different angles of the Experimental Setup

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

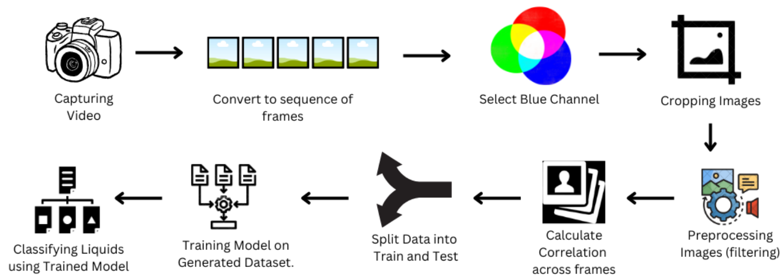
To maintain consistent environmental conditions across all tests, each liquid sample was measured at **room temperature** and in a controlled **relative humidity** environment. Given that temperature and humidity can significantly influence viscosity, these conditions were essential for obtaining reliable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

Our selection criteria for the liquids are limited to the fact that the speckle pattern created by the low-powered LiDAR scanner in the iPhone is primarily observed from the surface of the liquid rather than the liquid itself, which, as a result, will produce a much weaker signal and is harder to visualize. Keeping this in mind, we have selected the following five readily available liquids with



(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.

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 proxy for its viscosity, serving as a basis for classifying and detecting adulterants in liquids.

4.4 Laser-Speckle Pattern Analysis

The iPhone LiDAR scanner emits **NIR** laser pulses in a **24×24** grid pattern. When laser pulses hit a liquid droplet, the scattered light creates speckle patterns as a result of the particles suspended in the liquid. The characteristics of these patterns differ based on whether the laser targets a liquid surface or a solid one.

- **Solid Surface**: These surfaces produce *static speckle* as they distinctly correspond to the texture of the surface.
- **Liquid Surface**: In contrast, laser interaction with a liquid creates *dynamic speckle* patterns due to the Brownian motion of particles in the liquid. This time-dependent variation in speckle pattern is fundamental for liquid classification, as it reflects their viscosity characteristics.

This approach enables us to calculate the viscosity coefficients of each liquid using a two-dimensional correlation analysis among the video frames at each point in time (see 5.6).

Note that the coefficient value serves as a proxy for viscosity since determining it requires knowledge of the liquid's physical properties like particle size, etc.

5 METHODOLOGY

The liquid classification approach utilizing iPhone's LiDAR technology is organized into a structured workflow consisting of seven key stages, as depicted in Fig.2a.

5.1 Video Capture

The process begins with video data acquisition using a controlled setup. An iPhone 15 Pro Max LiDAR projects a 24×24 grid of NIR laser pulses onto liquid samples (10−50 μL) placed 8 cm from the LiDAR source on a glass slide. A Raspberry Pi NoIR Camera V2 records at 30 fps under regulated conditions, including room temperature, controlled humidity, a non-reflective surface, and minimal background lighting. The camera settings are optimized with a 1/30s shutter speed and 2x zoom to ensure image clarity and stability during data acquisition.

5.2 Frame Sequence Generation

The captured videos are processed by converting each 30-second recording into individual frames, with the first and last 2 seconds removed to eliminate transitional movements. Frames are extracted at a rate of 30 fps to ensure optimal pattern analysis and stored in sequential order for subsequent processing.

5.3 Blue Channel Selection

Color channel processing is applied to optimize speckle pattern analysis by extracting the blue channel from RGB frames, enhancing the visibility of speckle patterns. The extracted blue channel data is then stored for feature extraction in subsequent analysis.

5.4 Image Cropping

Dynamic cropping is used to select the Region of Interest (ROI), identifying a square region that encompasses the entire liquid drop. This ROI is then applied consistently across all selected frames for final cropping.

5.5 Image Preprocessing

The cropped images undergo enhancement and filtering, removing static speckle patterns and applying a threshold of 80 to retain only usable images. Additionally, frames impacted by LiDAR flickering are filtered out to improve data quality.

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

To create and process the training dataset, images were collected from various liquid samples, including Milk, Mango juice, Tomato sauce, Kesar Pista ice cream, and Butterscotch ice cream. The dataset was then divided into training and testing sets to facilitate model evaluation. Feature extraction focused on analyzing speckle patterns, capturing intensity fluctuations, pattern correlations, and temporal variations as key characteristics. These extracted features served as inputs for training the classification model, enabling it to differentiate between liquid types based on the unique speckle signatures of each sample.

5.8 Liquid Classification

The final classification process applies the trained model to new liquid samples, using speckle pattern characteristics for classification. Performance is evaluated with metrics such as accuracy, precision, recall, and F1-score, and results are validated against known liquid properties. This methodology integrates hardware configuration, image processing, and machine learning to create a reliable, reproducible system for classifying liquids via LiDAR-generated speckle patterns, leveraging viscosity characteristics for accuracy.

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, and Tomato sauce.

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

The validation results showed:

- Overall accuracy: 80.56%.

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

- 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]:

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

The validation results demonstrated:

- Overall accuracy: 91.67%.
- 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. High accuracy in identifying tomato sauce (100% correct classification) (see Fig.3) and minor confusion is observed while classifying similar liquids (between Kesar Pista ice cream and Mango juice).

6.3.2 Two-Liquid Sub-Classification. Out of 36 samples, the classification model has only 4 misclassifications (see Fig.4), indicating high accuracy. It performed well in identifying the Kesar Pista category, correctly classifying 20 of 23 instances, with minimal false positives across categories. highlighting its robust performance.

6.4 Key Findings

The evaluation results demonstrate that the system achieves high accuracy, with 96% in multi-class classification and 89% in subclassifying ice cream flavors. The model shows robust performance across various liquid types, particularly with distinct features, and maintains consistent accuracy between validation and test sets, indicating strong generalization. Accuracy is notably higher when distinguishing between more distinct liquids (e.g., milk vs. sauce) than similar types (e.g., different ice cream flavors). These findings validate the effectiveness of our LiDAR-based approach for

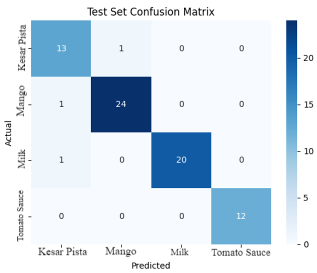


Figure 3: 4 Liquid Classification Confusion Matrix

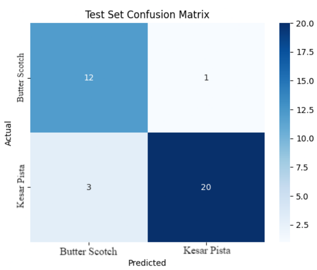


Figure 4: 2 Liquid Sub-Classification Confusion Matrix

liquid classification, excelling in distinguishing liquids with varying 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. Future work will expand the liquid database to include a wider range of substances and develop mobile applications for ease of deployment. Integration with IoT frameworks will support automated quality control while investigating temporal changes in liquid properties over time, which will enhance understanding of their stability for long-term applications.

7.2.2 Research Directions. Future efforts will explore advanced deep learning architectures for pattern recognition and investigate multi-modal sensing by combining LiDAR with other technologies. Studies will also assess the effects of temperature and environment on classification accuracy, along with analyzing micro-particle detection for contamination assessment.

7.3 Potential Applications

This technology holds potential for practical applications, including quality control in the food and beverage industry, pharmaceutical product verification, industrial liquid processing monitoring, consumer product authentication, and adulteration detection in commercial goods.

Future work will address current limitations and enhance system capabilities by developing advanced preprocessing algorithms for varied environments, incorporating temperature compensation for accurate viscosity assessment, expanding multi-parameter analysis, creating standardized testing protocols, and improving the classification model for a wider range of liquids. The promising results of this study set the stage for advancing non-contact liquid analysis using LiDAR, with smartphone LiDAR improvements expected to further boost accuracy and real-world applicability.

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