**Title: Fuzzy Labeled Private Set Intersection for Private Real-Time Biometric Search**

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**1. Introduction**

Biometric data is increasingly integral to secure identification and surveillance systems, offering unique advantages over traditional methods due to its accuracy and ease of use. However, the collection and processing of biometric data present critical privacy challenges, especially in real-time search scenarios where queries are performed against a sensitive, private biometric database. This research focuses on developing a privacy-preserving search protocol for biometric databases, termed **Fuzzy Labeled Private Set Intersection (FLPSI)**, which enables real-time matching under privacy constraints.

**Research Objectives**

* Develop a privacy-preserving search technique for biometric databases that allows matching without revealing non-relevant data.
* Implement fuzzy set matching to accommodate noise and variations in biometric data.
* Evaluate FLPSI’s effectiveness in both speed and accuracy, focusing on sublinear scaling for large databases.

**2. Methodology**

This study introduces the FLPSI protocol, which performs intersection on "fuzzy" (noisy or approximate) biometric data using a similarity metric rather than exact matching. The approach relies on:

* **Hamming Distance Representation**: Biometric images are mapped to Hamming space, where distances measure similarity.
* **Private Set Intersection (PSI)**: Secure cryptographic protocol allows two parties to find common elements without sharing the complete data set.
* **Fuzzy Matching**: Incorporates a tolerance level in matching criteria to allow slight differences between biometric features.

**Why This Method**: By combining fuzzy matching with PSI, FLPSI enables privacy-preserving search for real-time biometric identification, which is not achievable with traditional exact-match PSI methods. It’s an innovative solution that balances performance and security in high-speed network scenarios, addressing challenges in accuracy and data sensitivity.

**3. Implications**

The implications of FLPSI are significant:

* **Enhanced Privacy**: Organizations can perform biometric identification without exposing or compromising database information.
* **Broad Applications**: Potential use cases include secure biometric authentication, law enforcement databases, and sensitive health data matching.
* **Scalability**: This method is efficient and can handle large datasets, making it suitable for high-traffic applications such as airport security checks.

**4. Limitations**

Despite its potential, FLPSI has some limitations:

* **Computational Overhead**: While optimized, PSI processes still introduce non-trivial overhead, which may be limiting in low-resource environments.
* **False Positives and Negatives**: As with any fuzzy matching, there’s a possibility of errors in matching rates.
* **Scalability in Extreme Cases**: Very large databases (e.g., over 1M entries) may still experience latency that affects real-time usage.

**5. Advantages**

FLPSI’s advantages make it highly suited for real-time privacy-preserving applications:

* **Improved Matching Flexibility**: Fuzzy matching allows for small variations, which are common in biometric data due to environmental conditions or device variations.
* **Efficient Communication**: By optimizing data transfer, FLPSI is faster than traditional methods over wide-area networks (WANs).
* **Scalable Privacy**: Maintains privacy of both query and database entries, allowing biometric data to remain secure even in large-scale implementations.

**6. Python Code Implementation**

Below is a simplified version of FLPSI implemented in Python, demonstrating fuzzy matching in a synthetic database using Hamming distances.

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| python  Copy code  import numpy as np  from sklearn.metrics import pairwise\_distances  import matplotlib.pyplot as plt  import seaborn as sns  # Generate synthetic biometric data (e.g., 128-bit binary hash for facial features)  np.random.seed(42)  database\_size = 1000  query\_size = 5  # Synthetic biometric database and query, represented in binary form  database = np.random.randint(0, 2, (database\_size, 128))  query = np.random.randint(0, 2, (query\_size, 128))  # Compute Hamming distances between each query and database entries  distances = pairwise\_distances(query, database, metric='hamming')  # Define a matching threshold (tolerance for "fuzziness")  threshold = 0.1 # Adjust as needed for higher/lower tolerance  # Find matches within the threshold  matches = distances < threshold  # Display results for the first query  match\_count = np.sum(matches[0])  print(f"Matches found for first query within threshold: {match\_count}")  # Visualization of matches for the first query  plt.figure(figsize=(10, 6))  sns.heatmap(matches[0].reshape(1, -1), cmap='coolwarm', cbar=True)  plt.title(f'Matching Results for First Query with Threshold: {threshold}')  plt.xlabel('Database Entries')  plt.ylabel('Query')  plt.show() |

**Explanation of Code**

* **Synthetic Data Creation**: Generates random binary arrays to represent hashed biometric data.
* **Hamming Distance Calculation**: Measures similarity between query and database entries.
* **Threshold-Based Matching**: Applies a threshold to determine matches based on similarity, representing the "fuzziness" aspect.
* **Visualization**: Uses a heatmap to show which database entries match the query.

**7. Visualizations**

1. **Heatmap of Matching Results**: Displays where matches occur in the database for a given query. Helps in understanding distribution and quality of matches.
2. **Performance Analysis**: Graphs comparing query times and data transfer rates for various database sizes. These visualizations can be created by running the code with different parameters and recording execution times.

**8. Conclusion and Future Research**

FLPSI presents a robust solution for privacy-preserving, real-time biometric searches. This work contributes to cybersecurity by enabling fuzzy matching in a secure manner, thus supporting real-world scenarios where exact matches are not feasible. Future research can focus on:

* Optimizing computational efficiency for ultra-large databases.
* Exploring adaptive thresholds to improve accuracy across different biometric types.
* Investigating the integration of FLPSI with other secure multi-party computation protocols.

**References**

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