Real-time Pattern Isolation and Recognition Over Immersive Sensor Data Streams

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Outline

- Motivation
- Target Application
- Related Work
- Weighted-sum SVD
- The Ridge-Climbing Heuristic
- Performance Evaluation
- Conclusion & Future Work
Motivation

With traditional DBMS
- Dataset is persistent
- It operate on the entire dataset

In many recent applications
- Data (continuous data streams, CDS) constantly change or continuously arriving (e.g., web clickstreams, IP packets)
- Challenges:
  - Queries must be answered based on limited amount of information
  - Queries need to be answered in real time
  - Query results may need to be aggregated from different sources (e.g., the yahoo web page with the maximum number of hits)
Immersive Environments allow a user to become immersed within an augmented or virtual reality environment in order to interact with people, objects, places, and databases [ACM-ITP’02].

Immersidata Data acquired from user’s interaction with the immersive environment [CIDR’03].
Immersive Sensor Data Streams

Table 1: CyberGrasp Sensors

<table>
<thead>
<tr>
<th>Sensor Number</th>
<th>Sensor Description</th>
<th>Sensor Number</th>
<th>Sensor Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Thumb roll sensor</td>
<td>15</td>
<td>Ring middle abduction</td>
</tr>
<tr>
<td>2</td>
<td>Thumb inner joint</td>
<td>16,17,18</td>
<td>Pinky inner, middle, outer joint</td>
</tr>
<tr>
<td>3</td>
<td>Thumb outer joint</td>
<td>19</td>
<td>Pinky ring abduction</td>
</tr>
<tr>
<td>4</td>
<td>Thumb index abduction</td>
<td>20</td>
<td>Palm arch</td>
</tr>
<tr>
<td>5,6,7</td>
<td>Index inner, middle, outer joint</td>
<td>21</td>
<td>Wrist flexion</td>
</tr>
<tr>
<td>8,9,10</td>
<td>Middle inner, middle, outer joint</td>
<td>22</td>
<td>Wrist abduction</td>
</tr>
<tr>
<td>11</td>
<td>Middle index abduction</td>
<td>23,24,25</td>
<td>X,y,z location</td>
</tr>
<tr>
<td>12,13,14</td>
<td>Ring inner, middle, outer joint</td>
<td>26,27,28</td>
<td>X,y,z abduction</td>
</tr>
<tr>
<td></td>
<td></td>
<td>29 to 33</td>
<td>Forces for each finger</td>
</tr>
</tbody>
</table>

\[ <S_i, x, y, z, t, v> \]
Focus: American Sign Language (ASL) Recognition

Extra challenges (to CDS)
- A hand sign is composed by a sequence of data samples
- A sequence for one sign has no fixed length
- The data rates of sensors are fixed
- Data need to be “tightly” integrated and hence are high dimensional

An example statement in American Sign Language (ASL)

Two problems (chicken & egg-problem) with interdependent solutions should be addressed
- Isolate signs
- Recognize the isolated sign
Isolation/Recognition Processes

1. User makes ASL signs w/ a glove

2. Sensor values sampled over time

3. Accumulated similarity values

Recognition module:
- Weighted-Sum SVD

Isolation module:
- Ridge-Climbing Heuristic

4. Isolate the streams
Related Work

Research efforts on querying over CDS
- DBMS support, e.g., Stream [Babu&Widom 2001], Fjords [Madden&Frankin, 2002]
- Query processing and data mining issues [Hulten 2001; Guha 2000]
- Pattern recognition in one dimensional time series [Gao&Wang 2002]
- No studies on pattern recognition over aggregated and high dimensional CDS

Distance measures for the similarity queries
- Euclidean distance ∋ dimensionality curse
- Discrete Wavelet transform
- Discrete Fourier transform ∋ our dataset are no correlated on sensor dimension at any given time
The idea of SVD is based on the following theorem of linear algebra:

- If matrix \( X \in \mathbb{R}^{m \times n} \), then there exist column-orthonormal matrices \( U \) and \( V \) such that \( X = U \times A \times V^T \), where \( U \in \mathbb{R}^{m \times r} \) and \( V \in \mathbb{R}^{r \times n} \), and \( A \in \mathbb{R}^{r \times r} \) is a diagonal matrix \( A = \text{diag}(a_1, a_2, \ldots, a_p) \) such that \( a_1 \geq a_2 \geq \ldots \geq a_p \).
Each data sequence could be represented as a matrix, where the columns (r) are the sensors and hence their # is fixed.

The similarity metric of two data sequences is defined on the ‘square’ matrices.

- To eliminate the effect that the number of rows (i.e., the time dimension) in the two matrices are different (i.e., multiply the matrix by its transpose matrix)
Weighted-Sum SVD

Problem: Obtain the similarity of input sequence and the pattern.

\[ q_{11} \quad q_{1r} \]
\[ q_{r1} \quad q_{rr} \]

\[ p_{11} \quad p_{1r} \]
\[ p_{r1} \quad p_{rr} \]

SVD decompose

\[ e_1, e_2, \ldots, e_r \]
\[ c_1 \quad c_2 \quad \ldots \quad c_r \]
\[ e_1 \quad e_2 \quad \ldots \quad e_r \]

Weight

\[ c_1 \quad c_2 \quad \ldots \quad c_r \]
\[ f_1 \quad f_2 \quad \ldots \quad f_r \]
\[ d_1 \quad d_2 \quad \ldots \quad d_r \]
\[ f_1 \quad f_2 \quad \ldots \quad f_r \]

SVD decompose

\[ c_1 \quad c_2 \quad \ldots \quad c_r \]
\[ d_1 \quad d_2 \quad \ldots \quad d_r \]

\[ e_1 \quad e_2 \quad \ldots \quad e_r \]

\[ d_1 \quad d_2 \quad \ldots \quad d_r \]

\[ e_1 \quad e_2 \quad \ldots \quad e_r \]

\[ c_1 \quad c_2 \quad \ldots \quad c_r \]

\[ d_1 \quad d_2 \quad \ldots \quad d_r \]

\[ e_1 \quad e_2 \quad \ldots \quad e_r \]

\[ d_1 \quad d_2 \quad \ldots \quad d_r \]

\[ e_1 \quad e_2 \quad \ldots \quad e_r \]

\[ d_1 \quad d_2 \quad \ldots \quad d_r \]

\[ e_1 \quad e_2 \quad \ldots \quad e_r \]

\[ d_1 \quad d_2 \quad \ldots \quad d_r \]

\[ e_1 \quad e_2 \quad \ldots \quad e_r \]

\[ d_1 \quad d_2 \quad \ldots \quad d_r \]

\[ e_1 \quad e_2 \quad \ldots \quad e_r \]
Weighted-Sum SVD

Problem: Obtain the similarity of input sequence and the pattern

\[ \theta_1 = \sum_{i=1}^{r} cw_i (e_i \cdot f_i) \]
\[ \theta_2 = \sum_{i=1}^{r} dw_i (e_i \cdot f_i) \]

The similarity of input sequence and the pattern

= \min(T_1, T_2)
The Ridge-Climbing Heuristic

- Designed based on
  - Mutual information [Resa, 1961]
  - Observation: if the sequence $B$ should be detected as $K$, the accumulated similarity value between $B$ and $K$ will be monotonically increasing up to some time instance and then starts decreasing
The Ridge-Climbing Heuristic

Procedure:
- Compute the accumulated similarity values (ASVs) between the input sequence and all vocabulary sequences
- Keep track of all ASVs
- For each vocabulary sequence, check whether the ASV is monotonically increasing, and whether a maximum is reached
  - Yes: put this vocabulary into the candidates pool
- Choose the vocabulary from the candidates pool with biggest maximal value
- Isolate the recognized stream
The Ridge-Climbing Heuristic

Assume the database only has three vocabulary sequence, *like*, *yellow*, and *I*.

Input sequence

Maximum is reached!
Isolate!
Reset the ASVs

![Diagram](image)
Experimental Setup

Training
- Collect data from ten different people
- Each perform ten different color signs
- Obtain sign representatives

Testing
- User performed ten color sign combinations, e.g., Green-Orange-Yellow
## Compare similarity metric

<table>
<thead>
<tr>
<th></th>
<th>Yellow</th>
<th>Orange</th>
<th>Black</th>
<th>Red</th>
<th>Green</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yellow</td>
<td>0.965484</td>
<td>0.472714</td>
<td>0.427958</td>
<td>0.516680</td>
<td>0.480699</td>
</tr>
<tr>
<td>Orange</td>
<td>0.472714</td>
<td>0.946117</td>
<td>0.684033</td>
<td>0.546006</td>
<td>0.470286</td>
</tr>
<tr>
<td>Black</td>
<td>0.427958</td>
<td>0.684033</td>
<td>0.930344</td>
<td>0.886402</td>
<td>0.764338</td>
</tr>
<tr>
<td>Red</td>
<td>0.516680</td>
<td>0.546006</td>
<td>0.896402</td>
<td>0.960748</td>
<td>0.845138</td>
</tr>
<tr>
<td>Green</td>
<td>0.480699</td>
<td>0.470286</td>
<td>0.764338</td>
<td>0.845138</td>
<td>0.980830</td>
</tr>
</tbody>
</table>
Sign Combination
Sign Combination

Yellow-Black Stream

Black-Blue Stream
Conclusion & Future Work

Conclusion

- Propose “weighted-sum SVD” to measure the similarity of immersive sequences
  - Apply in immersive interaction application
  - Effectively handle high-dimensional data
- Propose “the Ridge-Climbing Heuristic” for tackling the problem of sequence separation over CDS
  - Experiments demonstrated this method is an appropriate mathematical abstraction

Future work

- Explore techniques for computing SVD incrementally
- Evaluate the effectiveness of different similarity metrics
Thank You!
References


