Query by Content for Time Series Data in RDBMS

INES F. VEGA-LOPEZ



University of Houston, Computer Science Seminar

12/6/13

Roadmap

2

Querying non-text data

- Time series data
- ECG data
- ECG sequence classification
- Extending RDBMS

Non-text data

- Music
- Speech
- Biosignals
- Images
- Video

Querying non-text data

• By describing content

- Query by associated text
- o Labels, html, etc.

• By content

- o Similarity search
- Similarity or distance function is required
- Provided by a domain expert

Roadmap

- Querying non-text data
- Time series data
- ECG data
- ECG sequence classification
- Extending RDBMS

Time series data

• A sequence of pairs (t[i], v[i])

• A timestamp and a value.

- o Delta t is usually constant.
- Sometimes, the absolute time value is not important.
- Then, the time series is just a sequence of values.

Time series data

- Querying have been well studied for the past 20 years
- Two types of queries
 - Whole sequence match
 - Subsequence match

Similarity Search on Time Series Data

• Whole Sequence Match

- Given a query pattern q of length n, and a DB, B, of sequences of legth n
- Find all $b \in B$ such that

$Dist(q,b) \leq \varepsilon$

University of Houston, Computer Science Seminar

Similarity Search on Time Series Data

Sub Sequence Match

- Given a query pattern q of length n, and a DB, B, of sequences of arbitrary length (each one longer than q)
- Find all pairs (b, i), $b \in B$, such that

$Dist(q, b[i:i+n]) \le \varepsilon$

How can we do this efficiently?

• For conventional data, we build and index and use it to prune the search space.

• A linear order exists among the object in the DB.

- For time series, we do not have a linear ordering.
- We can treat a (sub) sequence as a point in *n*-space.
 - o *n* is too large
 - Curse of dimensionality

Searching for (sub) sequences

• Generic Multimedia Indexing: GEMINI

- Map database Objects into a feature space.
- Index the transformed objects using a SAM
- Transform query objects to the feature space
- Search in this feature space
- Filter out false positives

Mapping into a Feature Space

- DFT
- DWT
- PAA
- APCA
- SAX
- Etc.

Roadmap

- Querying non-text data
- Time series data
- ECG data
- ECG sequence classification
- Extending RDBMS

ECG Data

• We want to do KDD on time series.

- Let us concentrate on a particular domain.
- Medicine has a high social impact.
- ECG data has some very interesting challenges.

Can we build upon existing models? Can we use try and tested RDBMS'?

Issues Challenges with ECG data

- An ECG contains more than one signal
 - o Usually 2 or 12 leads
- Different ECG's might have different lengths
 A few minutes to a couple of days
- Different ECG's might have different sampling ratios
 128 Hz to 1 or 2 KHz
- Values' bit-depth might also vary among ECG's
 8 to 20 bits per value

What about database systems?

16

• All these characteristics can be captured by the ER model just fine.

• In turn, this model can be transformed into relation.

An instance of an ECG DB

id_paciente	fecha_nacimiento	genero
251257	1927-03-25	F
275917	1938-04-23	M
306936	1962-07-14	F
291713	1934-04-27	F
312304	1968-10-05	F
368056	1954-03-20	F
317911	1931-06-22	M
277371	1977-12-26	ļ F
285170	1947-02-20	M
278173	1946-04-25	M
270014	1936-09-15	M
301829	1992-10-13	ļ F
311457	1932-03-10	F
294203	1991-12-28	ļм

id_ecg	id_paciente	longitud	fecha_captura	tipo_estudio
1	251257	8399360	2011-03-28	Holter
2	275917	8893782	2011-03-25	Holter
3	306936	8060758	2011-03-29	Holter
4	291713	8432126	2011-03-23	Holter
5	312304	8421206	2011-03-21	Holter
6	368056	8486742	2011-03-21	Holter
7	317911	8311979	2011-03-21	Holter
8	277371	7984299	2011-03-21	Holter
9	285170	8426667	2011-03-17	Holter
10	278173	8262827	2011-03-28	Holter
11	270014	8377515	2011-03-28	Holter
12	301829	8486742	2011-03-22	Holter
13	311457	8055296	2011-03-21	Holter
14	294203	8262827	2011-03-16	Holter
			-	-

id_derivacion	id_ecg	signal_a
1	1	R0140754-sig-1.bin
2	1	R0140754-sig-2.bin
3	1	R0140754-sig-3.bin
4	2	R0131968-sig-1.bin
5	2	R0131968-sig-2.bin
6	2	R0131968-sig-3.bin
7	3	R0149361-sig-1.bin
8	3	R0149361-sig-2.bin
9	3	R0149361-sig-3.bin
10	4	R0098061-sig-1.bin
11	4	R0098061-sig-2.bin
12	4	R0098061-sig-3.bin
13	5	R0080099-sig-1.bin
14	5	R0080099-sig-2.bin

What needs to be done?

- The content of an ECG signal is not a conventional data type.
- We need to define operators on this type
 - What operators?
 - × Similarity Search
 - × Define a formal model

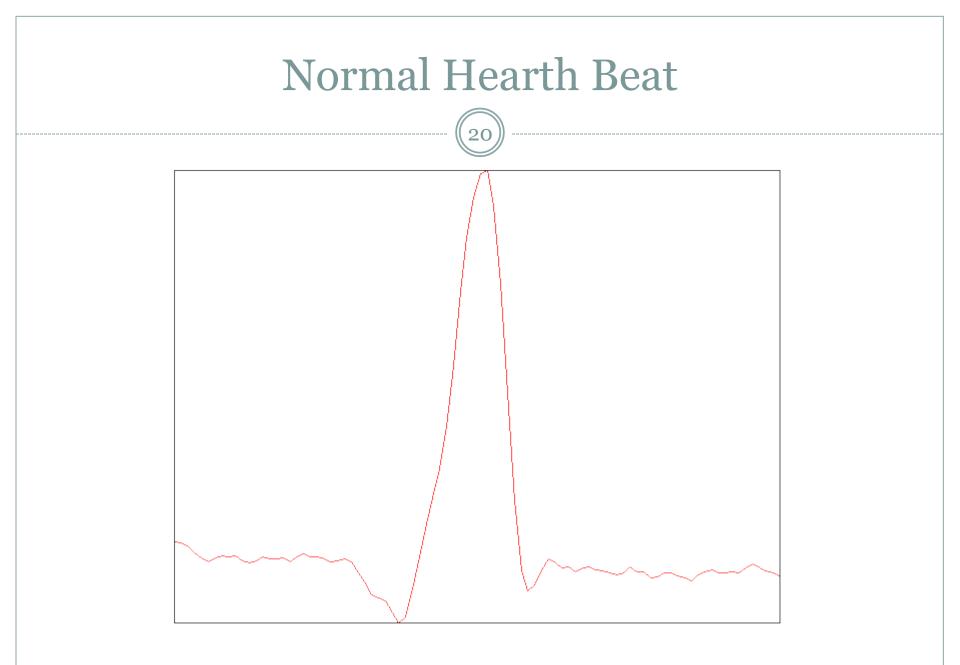
Roadmap

19

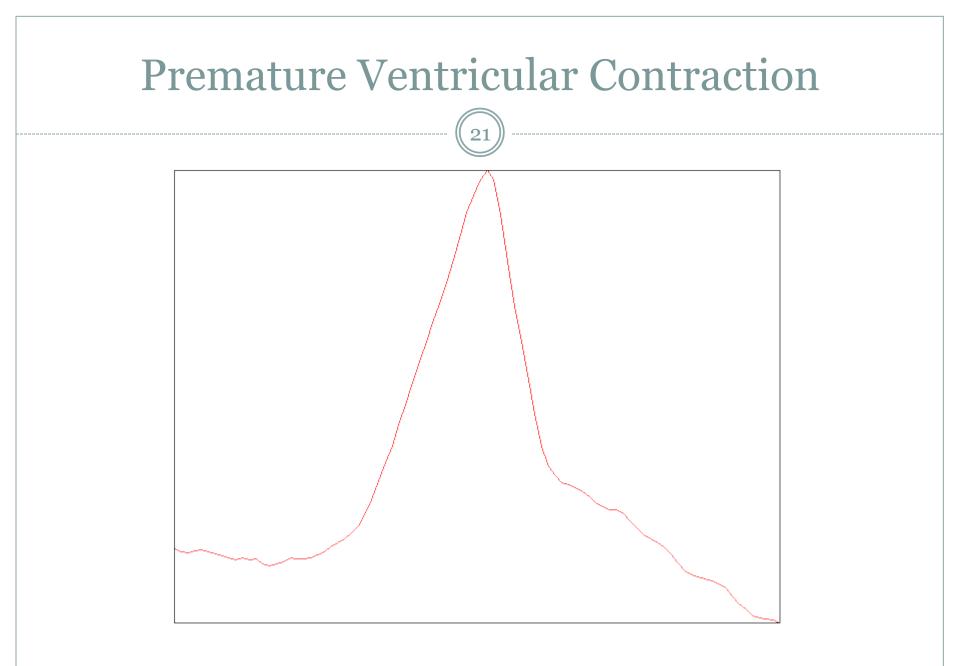
- Querying non-text data
- Time series data
- ECG data

ECG sequence classification

Extending RDBMS



University of Houston, Computer Science Seminar



Similarity Search

22

• K-nn search

• This gives us signals and the position of a matching subsequence

Subsequence retrieval

• This gives us the content of the matching signal

K-NN Search

23⁾

SELECT NN(D.signal, query_pattern, n)
FROM ECG_DATA D
WHERE <condition>;

Sub-sequence Fetch

24

SELECT subsequence(D.signal, position, n)
FROM ECG_DATA D
WHERE D.signal = signal id;

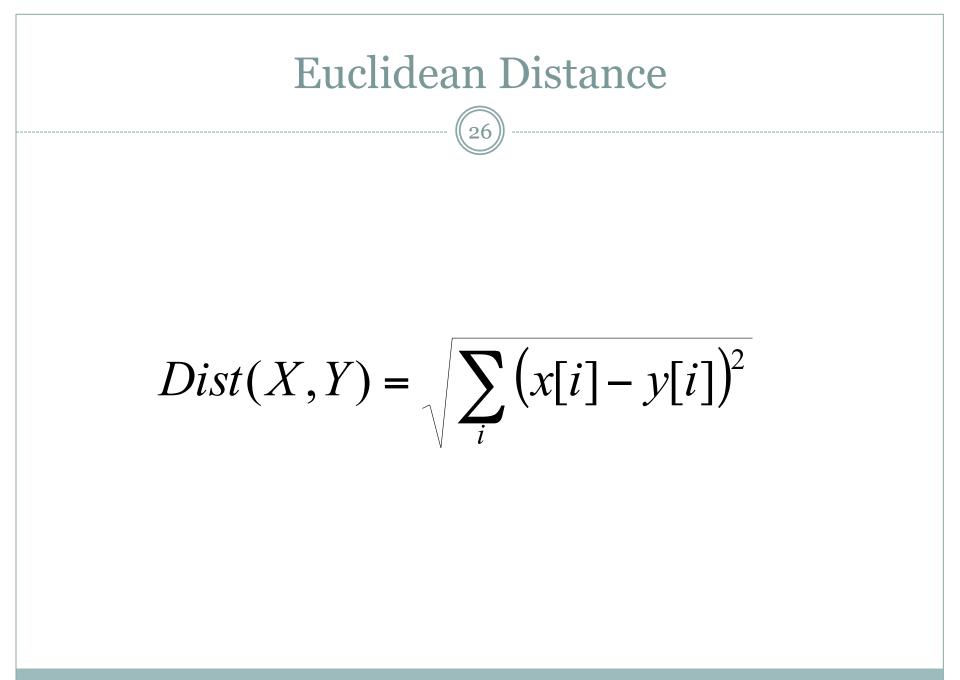
What about the Distance Function?

25

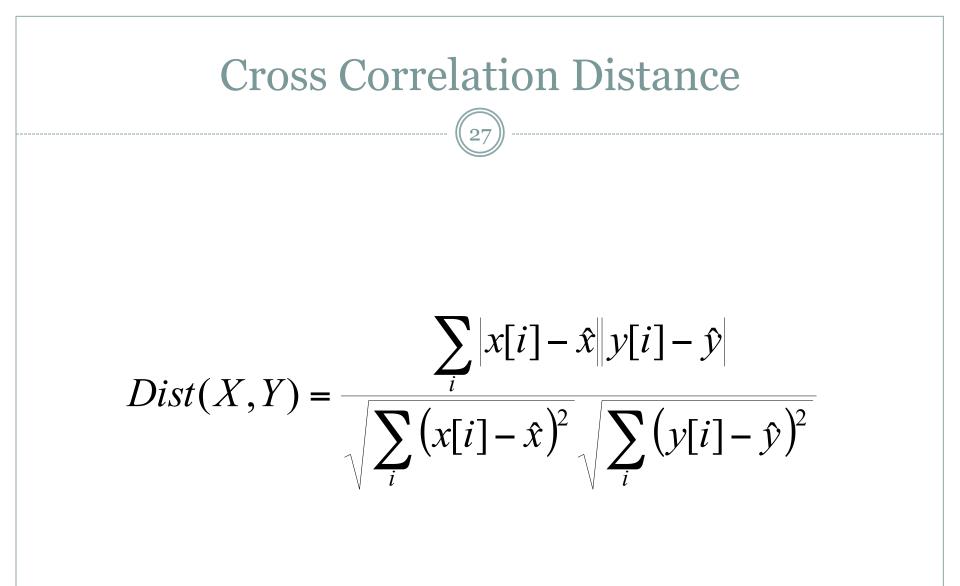
- For Querying Time Series, the DB community has been using L_p norm.
 - Most often Euclidean

Cardiologist use Cross Correlation

- This is not an L_P norm
- SAM's cannot be used.



University of Houston, Computer Science Seminar



12/6/13

Roadmap

- Querying non-text data
- Time series data
- ECG data
- ECG sequence classification
- Extending RDBMS

Similarity Searching with UDF

29

SELECT nn_ecg_file(s.valores_archivo, 'latido_ventricular_prematura.bin', 90)
FROM signal_d s;

resultado:

nn_ecg_file

/fcod-data-mitdb-223-signal-1.bin 561057 2.696500 (1 row)

Sub-sequence Fetch

30

SELECT subsequence(s.valores_archivo, 561057, 90) FROM signal_d s WHERE s.valores_archivo LIKE '%fcod-data-mitdb-223-signal-1.bin';

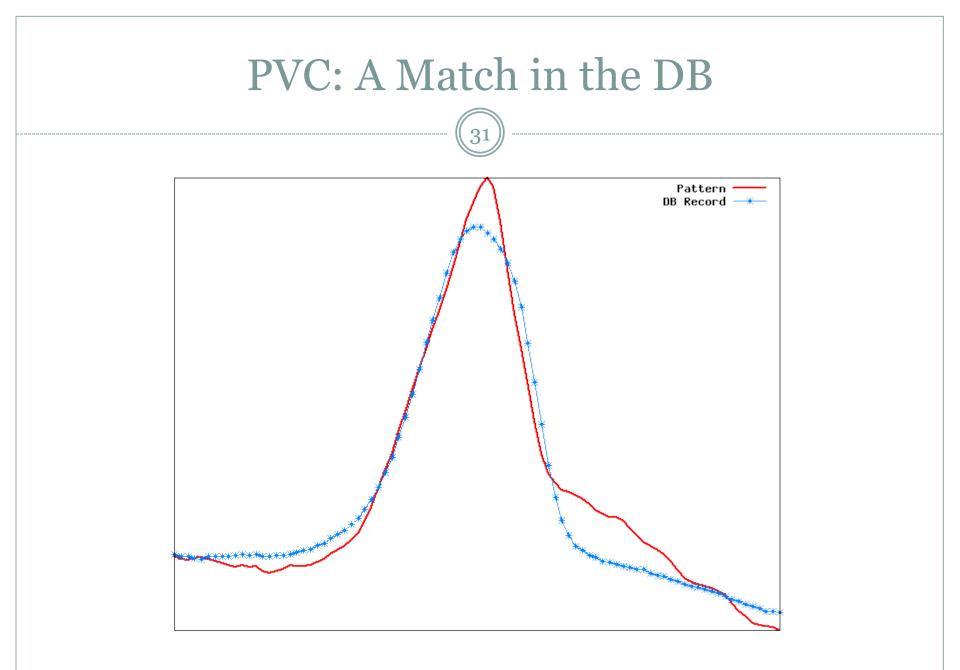
resultado:

subsequence

- 0 -0.580000
- 1 -0.595000
- 2 -0.595000
- 3 -0.605000
- 4 -0.610000
- 5 -0.595000
- 6 -0.595000
- 7 -0.595000
- 8 -0.590000
- 9 -0.585000
- 10 -0.575000
- 11 -0.585000
- 12 -0.580000
- 13 -0.595000
- 14 -0.595000
- 15 -0.585000

--More--(27%)

University of Houston, Computer Science Seminar



University of Houston, Computer Science Seminar

12/6/13

Which distance function is better?

- Using the MIT-BIH Arrhythmia DB
- For healthy non-healthy classification
 - o 98.35 % for Euclidean.
 - 98.59 % For Cross Correlation.
- For pathology classification (15 classes)
 - o 97.70 % For Euclidean.
 - o 98.14 % For Cross Correlation.
- Too close to call

Are UDF's Efficient?

- We stored ECG signals as BLOBs and as reference to a file.
- We developed an ad-hoc stand alone search application.
 - This uses a file repository.
- Using BLOBs has significant overhead both in storage (5X) and in total elapsed time (10X).
- UDF's on files are as efficient as ad-hoc queries.

Conclusions

34

- Similarity Search is complex because all data must be scanned.
 - It can be efficiently implemented to extend a RDBMS. Compared to an ad-hoc query.

• It is worth exploring GEMINI.

- Now that we now that Euclidean distance can be used.
- Data encoding should be considered.
 - We might not be getting much IO savings



University of Houston, Computer Science Seminar







University of Houston, Computer Science Seminar

