Mining Recurrent Items in Multimedia with Progressive Resolution Refinement

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Outline

- Introduction
- Multimedia association rules
- Frequent item-sets with recurrent items
- Mining multimedia association rules with spatial relationships
- Performance
- Discussion and conclusion

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Introduction

- Little research has been conducted on mining multimedia data
- Related works
  - CONQUEST
  - SKICAT
  - MultiMedia Miner
- Progressive refinement
  - mining multimedia association with recurrent objects
  - mining spatial relationships between visual descriptors

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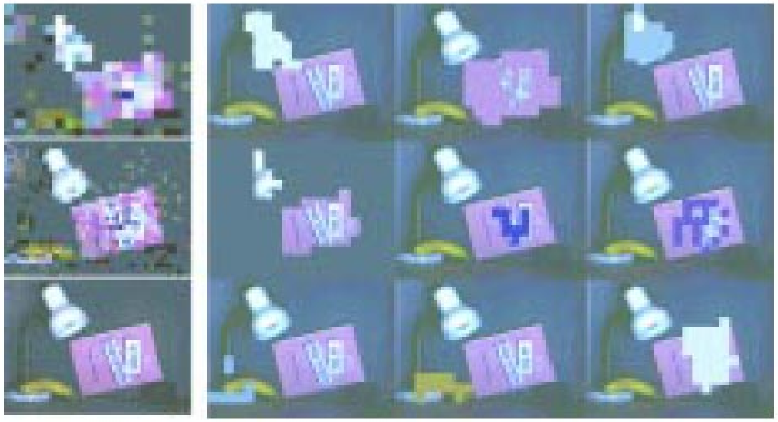
Multimedia association rules

- Image segmentation
  - regions are mostly connected
  - regions are disjoint
  - segmentation is complete
- Feature localization
  - a *locale* L_x is a local enclosure of feature x
  - L_x has a envelope Lx and some geometric parameters
  - Feature localization is a kind of rough segmentation.

Feature Localization



Multimedia associations with recurrent items

- Visual data has some peculiarities
  - e.g., Some visual features can occur multiple times in an image
  - repetition may carry more information
- An image can be modeled by a transaction
- Finding associations with a coarse-to-fine search strategy
  - save processing time
  - avoid too much detail/noise or insufficient detail

Multimedia associations with recurrent items (cont.)

- Apriori: Duplicates are never considered when k-item candidate sets C_k are formed
- In multimedia mining
  - *2 blue circles ⇒ high texture density*
  - Two occurrences have to co-exist in the image for the rule to be valid
- Two notions of *support*
  - Transaction-based support
  - Objected-based support

Multimedia associations with recurrent items (cont.)

- Multimedia associations rule with recurrent items

$$\alpha P_1 \wedge \beta P_2 \wedge \ldots \wedge \gamma P_n \rightarrow \delta Q_1 \wedge \lambda Q_2 \ldots u Q_m (c\%)$$

- A pattern p is sufficiently frequent in a set D at level l if the support of p is no less than its corresponding minimum support threshold and no more than its corresponding maximum support threshold
- A multimedia association rule P→Q in a set of images D is sufficiently strong in D if P and Q are sufficiently frequent and the confidence of P→Q is greater than the threshold φ`

Multimedia associations with recurrent items (cont.)

Two types of multimedia association rules:

- content-based multimedia association rules with recurrent visual descriptors (based only on atomic visual features)
- multimedia association rules with recurrent spatial relationships (uses the topological relationships between locales)
  - v-next-to: vertical closeness
  - h-next-to: horizontal closeness
  - overlap
  - include

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Frequent item-sets with recurrent items

- A naïve approach

Image ID	Object ID	Colour	Texture	[illegible]	Shape	Motion	...
I_1	$O_{(1,1)}$	$Colour_1$	$Texture_1$	[illegible]	$Shape_1$	[illegible]	...
I_1	$O_{(1,2)}$	...	...	...	...	...	...
...							
I_2	$O_{(2,1)}$	...	...	...	...	...	...
...							
I_n	$O_{(n,m)}$	...					

Table 1. Relation with Visual Atomic Features.

Image ID	Object ID	V-Next-to	H-Next-to	Overlap	Include
I_1	$O_{(1,1)}$	[illegible]	[illegible]	[illegible]	{}
I_1	$O_{(1,2)}$	{...}	{...}	{...}	{...}
I_n	$O_{(n,m)}$	...			

Table 2. Relation with Spatial Relationships.

Frequent item-sets with recurrent items (cont.)

- A naïve approach
  - Find all frequent 1-item-sets
  - check how often they might re-occur in an image (maximum occurrence)
  - For each k-item-set, combine these frequent 1-item-sets in the sets of k elements
  - The calculation of the support would filter out the infrequent ones

This naïve algorithm guarantees to find all frequent item-sets with recurrent items.

MaxOccur algorithm

Image ID	Objects
I_1	$\{O_2, O_2, O_2, O_4, O_5\}$
I_2	$\{O_2, O_2, O_4, O_4\}$
I_3	$\{O_2, O_3, O_4\}$
I_4	$\{O_6, O_7\}$
I_5	$\{O_1, O_2, O_2, O_3, O_4, O_4\}$

Object	Support	Max. Occurrence
$\{O_1\}$	1	1
$\{O_2\}$	8	3
$\{O_3\}$	2	1
$\{O_4\}$	6	2
$\{O_5\}$	1	1
$\{O_6\}$	1	1
$\{O_7\}$	1	1

Table 3. Top: Image transaction table $\mathcal{D}_1$. Bottom: C_1 and M tables.

MaxOccur algorithm (cont.)

Object	Support	Max. Occurrence
$\{O_2\}$	8	3
$\{O_3\}$	2	1
$\{O_4\}$	6	2

Image ID	Sufficiently Frequent Objects
I_1	$\{O_2, O_2, O_2, O_4\}$
I_2	$\{O_2, O_2, O_4, O_4\}$
I_3	$\{O_2, O_3, O_4\}$
I_4	$\{O_2, O_2, O_3, O_4, O_4\}$

Table 4. Top: F_1 and M tables. Bottom: Filtered image transaction table $\mathcal{D}_2$.

MaxOccur algorithm (cont.)

2 item-sets	Support
$\{O_2, O_3\}$	2
$\{O_2, O_4\}$	6
$\{O_3, O_4\}$	2
$\{O_2, O_2\}$	3
$\{O_4, O_4\}$	2

2 item-sets	Support
$\{O_2, O_3\}$	2
$\{O_2, O_4\}$	6
$\{O_3, O_4\}$	2
$\{O_2, O_2\}$	3
$\{O_4, O_4\}$	2

Table 5. Candidate 2 item-sets C_2 and sufficiently frequent 2 item-sets F_2.

MaxOccur algorithm (cont.)

3 item-sets	Support
$\{O_2, O_3, O_4\}$	2
$\{O_2, O_2, O_3\}$	1
$\{O_2, O_2, O_4\}$	3
$\{O_2, O_4, O_4\}$	2
$\{O_3, O_4, O_4\}$	1
$\{O_2, O_2, O_2\}$	1

3 item-sets	Support
$\{O_2, O_3, O_4\}$	2
$\{O_2, O_2, O_4\}$	3
$\{O_2, O_4, O_4\}$	2

Table 6. Candidate 3 item-sets C_3 and sufficiently frequent 3 item-sets F_3.

MaxOccur algorithm (cont.)

4 item-sets	Support
$\{O_2, O_2, O_4, O_4\}$	2

4 item-sets	Support
$\{O_2, O_2, O_4, O_4\}$	2

Table 7. Candidate 4 item-sets C_4 and sufficiently frequent 4 item-sets F_4.

MaxOccur algorithm (cont.)

- Rules

(1) $\{O_4,O_4\} \to \{O_2,O_2\}$ [100%] (2) $\{O_2,O_4,O_4\} \to \{O_2\}$ [100%]

(3) $\{O_3,O_4\} \to \{O_2\}$ [100%] (4) $\{O_3\} \to \{O_2,O_4\}$ [100%]

(5) $\{O_2,O_2\} \to \{O_4\}$ [100%] (6) $\{O_4,O_4\} \to \{O_2\}$ [100%]

(7) $\{O_3\} \to \{O_2\}$ [100%] (8) $\{O_3\} \to \{O_4\}$ [100%]

- count replicated objects

$2O_4 \to 2O_2$ [100%], $O_2 \wedge 2O_4 \to O_2$ [100%], $O_3 \wedge O_4 \to O_2$ [100%],

$O_3 \to O_2 \wedge O_4$ [100%], $2O_2 \to O_4$[100%], $2O_4 \to O_2$ [100%],

$O_3 \to O_2$ [100%], $O_3 \to O_4$ [100%],

**** $O_4 \to O_2$ is not confident enough, while "$2O_4 \to 2O_2$" or "$2O_4 \to O_2$" are 100% reliable.*

MaxOccur algorithm (cont.)

begin
$C_1 \leftarrow \{\text{Candidate 1 item-sets and their } support\}$
$F_1 \leftarrow \{Sufficiently\ frequent \text{ 1 item-sets and their } support\}$
$M \leftarrow \{Maximum\ occurrence \text{ in an image of } frequent \text{ 1 item-sets}\}$
Count # of k-item-sets (total$[1..k]$)
for $(i \leftarrow 2; F_{i-1} \neq \emptyset; i \leftarrow i+1)$ $do\{$
    $C_i \leftarrow (F_{i-1} \bowtie F_{i-1}) \cup$
    $\{y \oplus X \mid X \in F_{i-1} \wedge y \in F_1 \wedge Count(y, X) < (M[y] - 1)\}$
    $C_i \leftarrow C_i - \{c \mid (i-1) \text{ item-set of } c \notin F_{i-1}\}$
    $\mathcal{D}_i \leftarrow FilterTable(\mathcal{D}_{i-1}, F_{i-1})$
    foreach image I in $\mathcal{D}_i$ do {
        foreach c in C_i do {
            $c.support \leftarrow c.support + Count(c, I)$
        }
    }
    $F_i \leftarrow \{c \in C_i \mid \frac{c.support}{total\ i\ itemset} > \sigma\prime\}$
}
Result $\leftarrow \bigcup_i \{c \in F_i \mid i > 1 \wedge c.support < \Sigma\prime\}$
end

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Mining multimedia association rules with spatial relationships

- Spatial predicates have two arguments
  - find frequent one and two-item-sets
  - combine the spatial predicates with only these item-sets
  - consider the result as the candidate 1-item-sets of the multimedia association rules with spatial relationship.
  - MaxOccur is then used to find the k-item-sets of frequent spatial predicates

For a spatial predicate P(X,Y) to be sufficiently frequent, X and Y have to be sufficiently frequent, and the 2-item-set {X,Y} has to be sufficiently frequent.

Mining multimedia association rules with spatial relationships (cont.)

- The naïve method would be to combine all pairs of object attributes at a given conceptual level and join them with all spatial predicates to derive potential 1-item-sets
- This would generate very large number of candidates
- The authors algorithm is to lessen the candidate set to the minimum before computing the frequent spatial predicate k-item-sets

Mining multimedia association rules with spatial relationships (cont.)

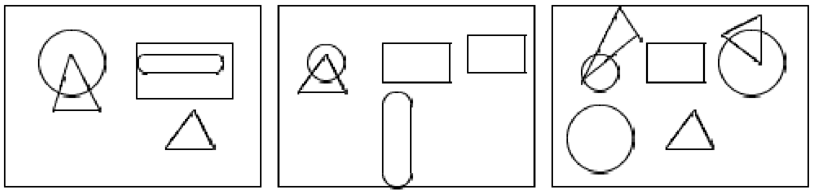

Figure 2. Examples of images with objects.

Mining multimedia association rules with spatial relationships (cont.)

Given minimum threshold 3

First scan: reveals only three frequent items ❡ ≅ □

second scan: reveals frequent pairs of items

(four spatial predicates: H-next-to, V-next-to,overlap,include)

Another scan:reveal 7 combinations are possible, compute their support and maximum occurrence in an image

Mining multimedia association rules with spatial relationships (cont.)

Pairs of Objects	Frequency
{○, ○}	1
{○, △}	3
{○, □}	3
{△, △}	2
{△, □}	3
{□, □}	1

1-item-set	Frequency	Max Occurrence
Overlap(○, △)	3	2
H-Next-to(○, △)	1	1
H-Next-to(○, □)	3	2
H-Next-to(△, □)	3	2
H-Next-to(□, □)	1	1
V-Next-to(○, △)	1	1
V-Next-to(△, □)	2	1

Table 8. Frequent pairs of objects and Frequent spatial predicates.

Mining multimedia association rules with spatial relationships (cont.)

Algorithm MM-Spatial

begin

(1) P1←{Frequent atomic items}

(2)P2 ←{Frequent pairs in P1*P1}

(3)C1 ←{P2*{spatial predicate set} and their support}

(4)F1 ←{Frequent 1 item-sets from C1}

(5)line 3 to 16 of MaxOccure

end

A progressive refinement methodology

- Multi-resolution strategy:
  - first find patterns at low resolution
  - persevere the search at a higher resolution with only the data selected in lower resolutions
  - Basic idea:quickly approximate patterns at a coarse level, then eliminate false positives by verifying them at a higher resolution

A progressive refinement methodology

Algorithm(PRR) Progressive Resolution Refinement for Mining Multimedia Association Rules

begin
(1)$i \leftarrow 0$ /* Lowest resolution level */
(2)$D_0 \leftarrow D$
(3)while (i<maximum resolution level) do /*Coarse to fine discovery */
(4)$R_i \leftarrow$ {r|r is a sufficiently frequent item-set at resolution level I(in D_i)}
(5)$i \leftarrow i+1$ /*Move to higher resolution level */
(6)$D_i \leftarrow$ Filter(D_{i-1},R_{i-1})
(7) }
end

A progressive refinement methodology

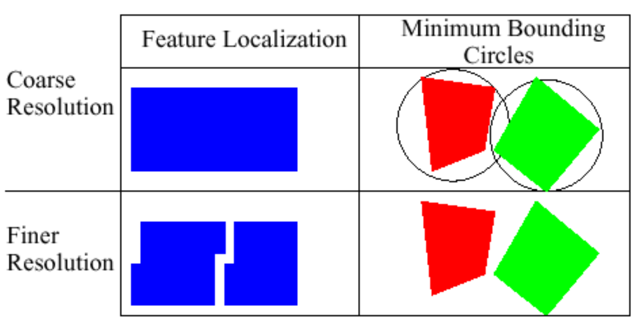

Figure 3. Relativity of visual feature concepts at different resolution levels.

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Performance

# of images	Apriori	Naïve	MaxOccur1	MaxOccur2
10K	6.43	78.91	13.62	13.68
25K	15.66	176.69	32.35	34.11
50K	38.54	359.38	66.07	67.44
75K	44.93	514.35	97.27	101.25
100K	60.75	716.01	138.12	137.81

Table 9. Average execution times in seconds with different number of images.

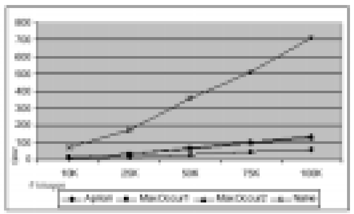

Figure 5. Scale up of the algorithms.

Performance

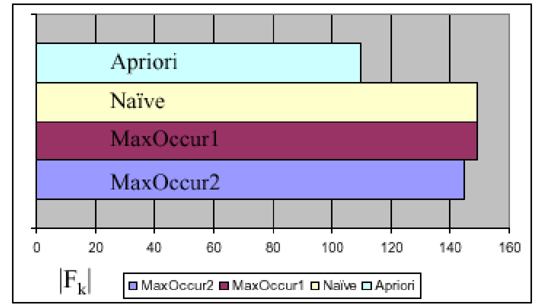

Figure 6. Frequent item-sets found by the different algorithms.

Discussion and conclusion

- Contribution of this paper
  - The authors introduced multimedia association rules based on image content and spatial relationships between visual features in images using coarse to fine resolution approach.
  - Progressive Resolution Refinement approach substantially reduced the overall data mining cost without loss of the quality and completeness of the results
  - Two algorithms for the discovery of content-based multimedia association rules.
- Discussion
  - Using meta-rule to enhance the performance
  - Using regions and their signatures
  - To recognize object in image processing
  - can be applied in many application domains