Robust Optical Recognition of Handwritten Musical Scores based on Background Knowledge

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About me

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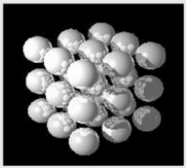
VCMI Group Member

http://vcmi.inescporto.pt/

School of Sciences, University of Porto.

Graduation: Mathematics Applied to Technology.

U. PORTO



FACULDADE DE CIÊNCIAS
Departamento de Matemática Aplicada

matemática aplicada à tecnologia

Master Degree: Mathematical Engineering.

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School of Engineering, University of Porto.

PhD: Electrical and Computer Engineering.

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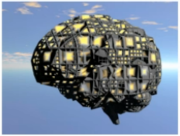
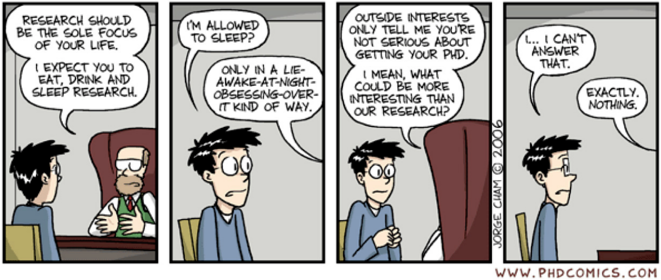


VCMI: Visual Computing and Machine Intelligence[1].

- A research group at INESC Porto.
- Research in computer vision, image processing, machine learning, and decision support systems.
- Focuses on medical images, documents with handwritten content and video object tracking.

[1] http://vcmi.inescporto.pt/

Obstacles.



- Oral presentations: english speaking.
- Write and read papers.

Robust Optical Recognition of Handwritten Musical Scores based on Background Knowledge

It is cruel, you know, that music should be so beautiful. It has the beauty of loneliness and of pain: of strength and freedom. The beauty of disappointment and never-satisfied love. The cruel beauty of nature, and everlasting beauty of monotony.
Benjamin Britten

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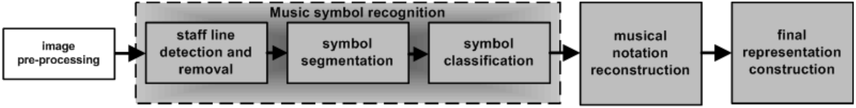
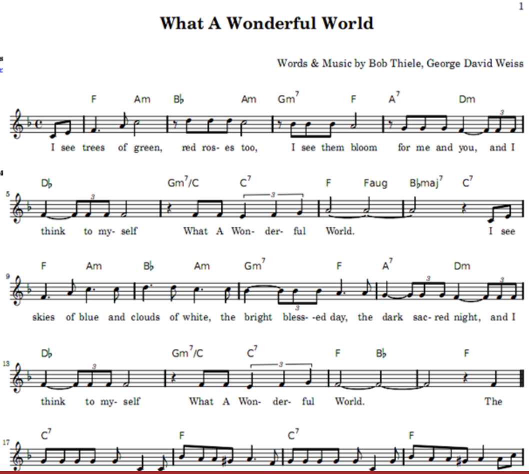
OMR Architecture.



Final Output.


```xml
<?xml version="1.0" encoding="UTF-8"?>
<!DOCTYPE score-partwise PUBLIC "-//Recordare//DTD MusicXML 2.0 Partwise//EN" "http://www.musicxml.org/dtds/partwise.dtd">
<score-partwise version="2.0">
    <work>
        <work-number></work-number>
        <work-title></work-title>
    </work>
    <movement-number></movement-number>
    <movement-title>What A Wonderful World</movement-title>
    <identification>
        <creator type="composer">Bob Thiele, George David Weiss
        <creator type="poet">Bob Thiele, George David Weiss</cr
        <rights>All Rights Reserved</rights>
        <encoding>
            <software>Sibelius 5.2</software>
            <software>Dolet 4 for Sibelius, Beta 2</software>
            <supports type="no" element="accidental"/>
            <supports type="no" element="transpose"/>
            <software>ProxyMusic 2.0 c</software>
        </encoding>
        <source>http://www.wikifonia.org/node/689/revisions/124
    </identification>
    <defaults>
        <scaling>
            <millimeters>6</millimeters>
            <tenths>40</tenths>
        </scaling>
        <page-layout>
            <page-height>1980</page-height>
            <page-width>1400</page-width>
        </page-layout>
    </defaults>
    <part-list>
        <score-part id="P1">
            <part-name> </part-name>
            <part-abbreviation> </part-abbreviation>
        </score-part>
    </part-list>
```

Database.

- 65 handwritten music scores from 6 different authors.
- References obtained manually.
- 32 printed scores to which know deformations where applied: 2688 images.
- Binarization stage: difference from reference threshold (DRT), missclassification error (ME), missed object pixel (MOPx) and false object pixel (FOPx).
- Staff line detection stage: the percentage of false positive and false negative.
- Music symbols extraction stage: precision, recall and accuracy.

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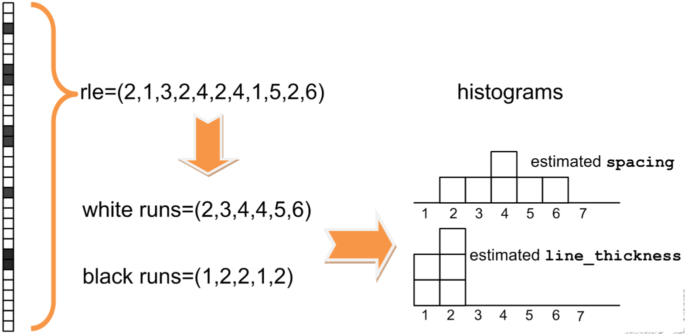
Staffline Distance and Thickness[2].

[2] "Robust staffline thickness and distance estimation in binary and gray-level music scores", J. S. Cardoso and A. Rebelo, *In Proceedings of The Twentieth International Conference on Pattern Recognition*, pages 1856–1859, 2010.

Conventional Estimation.



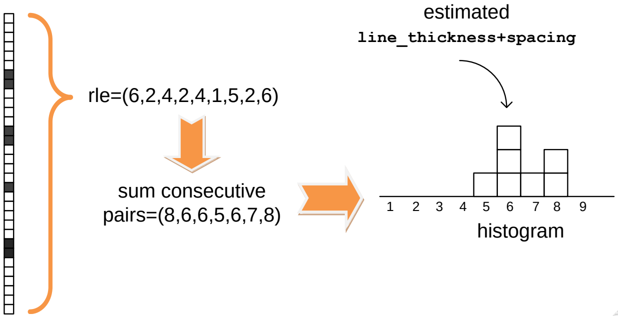
Example.

(a) Original music score #17.

(b) Score binarized with Otsu' method.

Figure: Unsuccessful estimation of staffline_height (=1) and staffspace_height(=1) by vertical runs.

Robust Estimation in Binary Images.

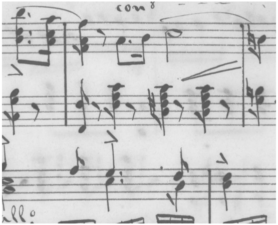


Results.

Table: Mean value of errors (in pixels) in the reference lengths.

Length	Error	conventional estimation in binary images	proposed estimation in binary images
staffline	mean	1.6	1.3
staffspace	mean	2.7	1.3
staffline+ staffspace	mean	2.4	0.4

Objective.



(a) Gray image.

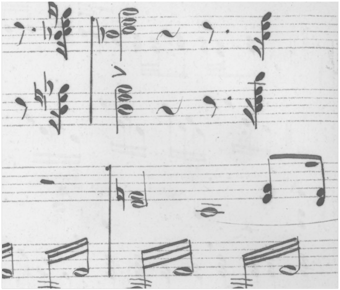
(b) Binary image.

Common Problems I.

(a) Gray image.

(b) Binary image.

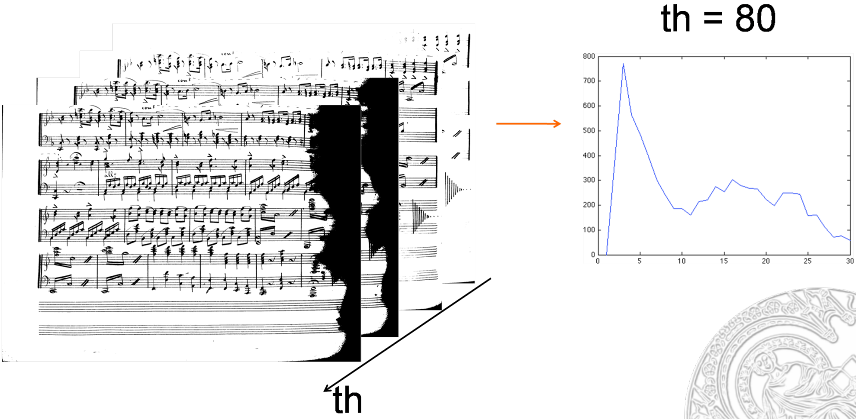
Common Problems II.



(a) Gray image.

(b) Binary image.

Binarization based in LIne Spacing and Thickness Algorithm[3].



[3] “Music score binarization based on domain knowledge”, Telmo Pinto, Ana Rebelo, Gilson Giraldi and Jaime S. Cardoso, in *In Proceedings of 5th Iberian Conference on Pattern Recognition and Image Analysis* (IbPRIA), 2011

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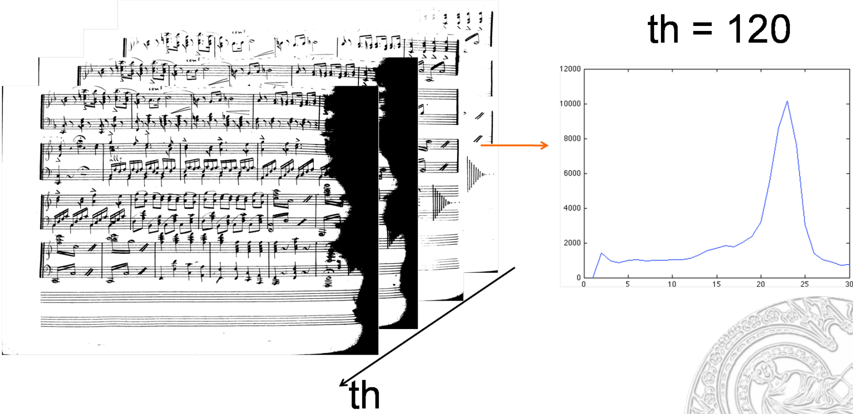

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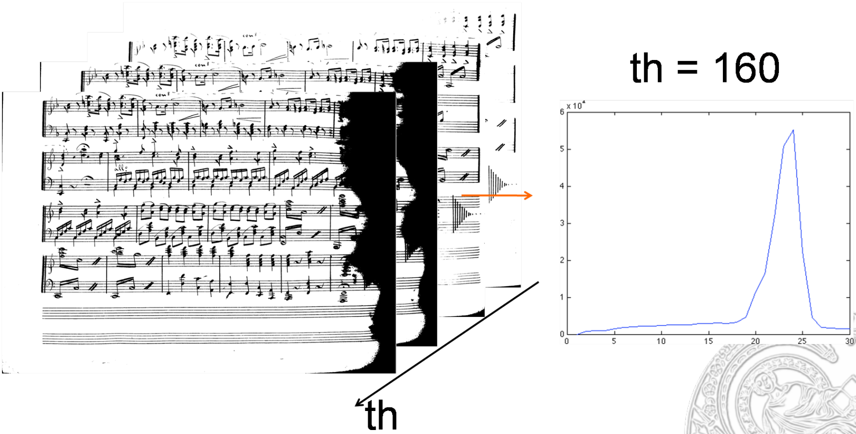

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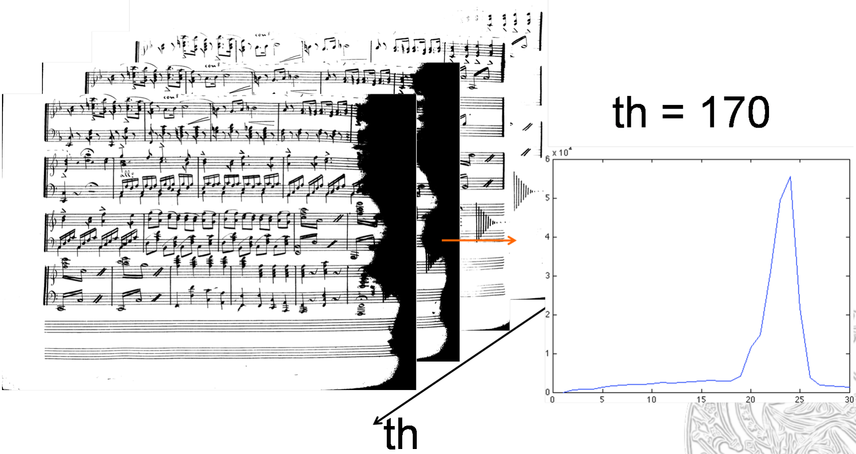

[3] "Music score ...
S. C...

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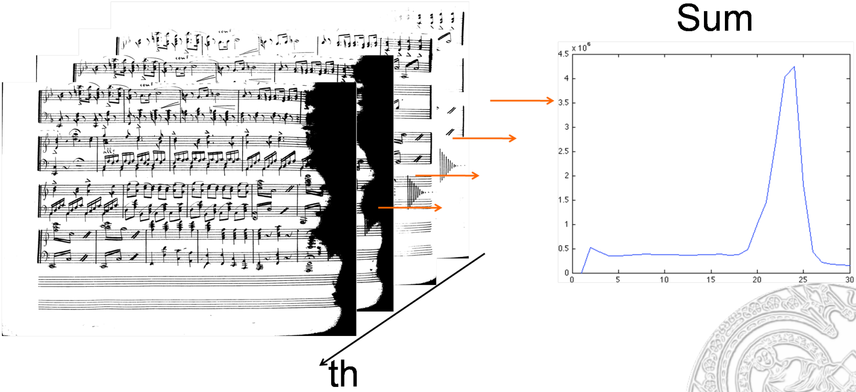

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BLIST Algorithm.

(Some) Results.

	Huang	Khashman	Kapur	Sahoo	Tsai	Tsallis	Otsu	BLIST pairs
DRT: avg	48	33	50	50	29	50	19	19
ME: avg %	6.2	3.8	4.9	7.6	4.7	5.7	4.6	4.8
SP False: avg(std) %	2.6(5.5)	2.1(4.0)	1.4(3.4)	3.5(10.2)	2.1(4.1)	3.3(7.4)	2.0(3.4)	1.3(2.7)
SP Missed: avg(std) %	18.0(34.5)	30.2(42.3)	27.1(42.3)	25.7(40.1)	17.0(30.3)	21.0(36.4)	8.6(20.5)	1.5(2.8)
Dal False: avg(std) %	21.6(41.1)	3.2(7.8)	1.8(4.2)	5.4(25.6)	4.4(8.1)	2.4(6.0)	3.6(5.4)	3.2(5.0)
Dal Missed: avg(std) %	39.6(36.9)	32.7(41.4)	31.2(42.0)	35.4(42.5)	25.4(35.0)	31.5(41.8)	18.8(31.0)	14.8(28.6)

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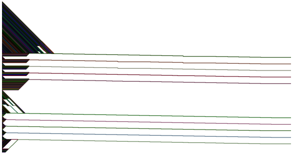
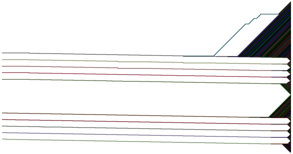
Stable Path Approach – Graphs[4].



(a) Shortest path between each pixel in the left column the whole right column.



(b) Shortest paths from each pixel in the right column and the whole left column.

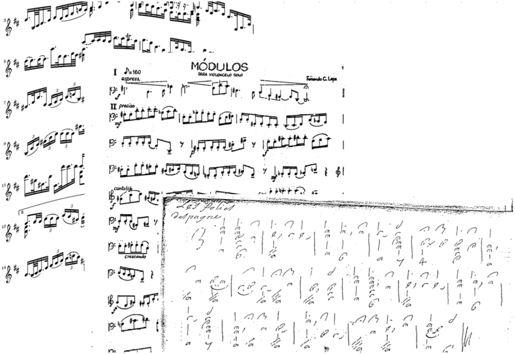
- Two approaches: shortest path and stable path.
- With the concept of Stable Paths, the computation of all the staff lines has only roughly twice the complexity of the shortest path computation.
- The stable paths concept provides a means to find all of shortest paths simultaneously: compute all the shortest path between the left margin and the whole right margin; in a second step repeat this process in a transverse way; at the end if the two endpoints of a direct and reverse graph coincide, we have a stable path.

[4] 'Staff Detection with Stable Paths", J. S. Cardoso, A. Capela, A. Rebelo, C. Guedes, J. Costa, in *IEEE Transaction on Pattern Analysis and Machine Intelligence*, volume 31, pages 1134–1139, 2009.

Stable Path Approach – Algorithm.

1. Preprocessing: Estimating the values *staffspaceheight* and *stafflineheight*; Estimating the edges' weights.
2. Successively finding the stable paths between the left and right margins, adding the paths found to a list and erasing them from the image.
3. Postprocessing: remove intersections, cluster lines in staves, remove spurius staves, smooth and trim the lines.

Staff Line Removal – Algorithm.



The algorithm tracks the staff lines and checks when a vertical black run is longer than a threshold (experimentally set a `stafflineheight`).

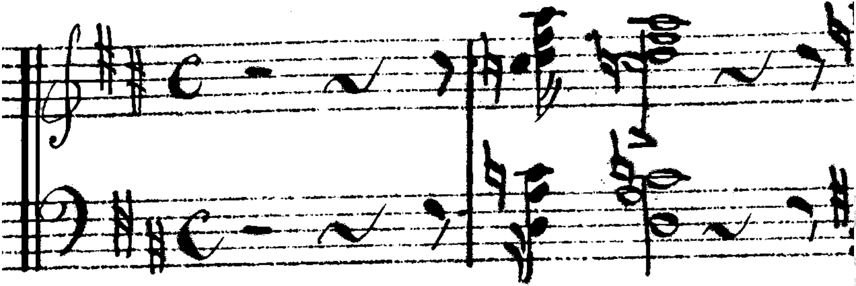
(Some) Results.

	False detection rate	miss detection rate	Runtime
Dalitz	5.2% (10.4)	5.9% (11.3)	112 sec.
Stable path	1.3% (5.7)	1.4% (6.4)	115 sec.

Table: Detection performance on real music scores in percentage: average (standard deviation).

Music Symbols Detection[5].

- Object: to localize and to isolate musical objects.
- Complex task: caused by printing and digitalization, the paper degradation over time and distortions in staff lines.

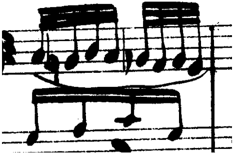


[5] "A Method for Music Symbols Extraction based on Musical Rules", A. Rebelo, F. Paszkiewicz, C. Guedes, A. R. S. Marcal, and J. S. Cardoso, in *In Bridges: Mathematical Connections in Art, Music, and Science*, 2011.

Broken, connected and overlapping symbols.

(a) Broken minim symbols.

(b) Connected notes in a chord.

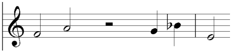


(c) A slur that overlapped a beam.

Variability in sizes and shapes between handwritten and printed scores.


(a)


(b)

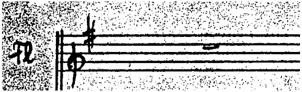

(c)


(d)

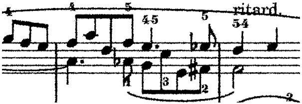

(e)


(f)

Noise and zones of high density of symbols.



(a) Music scores with noise.

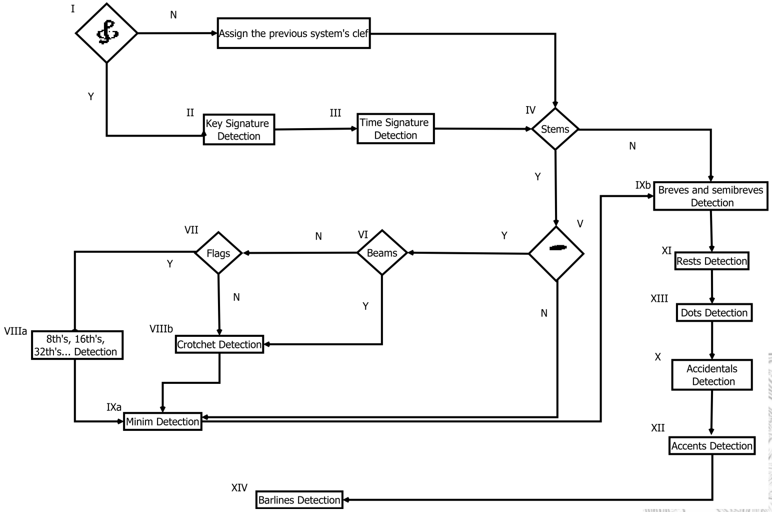


(b) An high density of symbols.

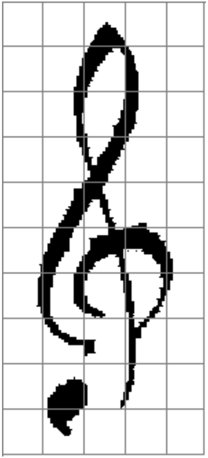
Music Symbols.

- Symbols that are characterized by a vertical segment (stem) and an oval note head: crotchet (e.g. ♩), notes with flags (e.g. ♪) and minim (e.g. 𝅗𝅥).
- Symbols that link the notes: beams (e.g. ♫).
- Symbols connected to staff lines: clefs, rests (e.g. 𝄾), accidentals (e.g. $\flat$, $\sharp$, $\natural$) and time signature (e.g. 𝄵).
- Symbols above and under staff lines: ties, slurs (e.g. $\frown$) and accents (e.g. $>$).

Architecture Algorithm.



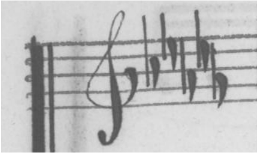
Implemented Solutions I - Matrix Correlation.



0	0	35	1	0
0	16	45	28	0
0	26	24	28	0
0	7	64	1	0
0	40	41	6	0
5	57	70	63	9
17	47	24	41	6
0	27	11	34	0
0	56	12	15	0
0	34	0	0	0

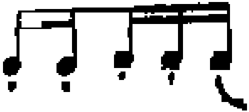
Implemented Solutions II - Music Rules.


(a)


(b)


(c)


(d)


(e)

(f)

Implemented Solutions III - Geometric Properties.

(a) Music score without stems.

(b) First noteheads detected.

(c) Noteheads with shape approximatly equal to a rectangle.

(d) Noteheads without white pixels inside them.

Implemented Solutions IV - Morphological Operations.

(a) (b) (c) (d)

Figure: Morphological operations applied to the rest symbols: (a) Original rest symbol; (b) Closed rest symbol; (c) Skeleton of the rest symbol; (d) Termination points of the rest symbol.

Results.

	Precision	**Recall**	**Accuracy**
Handwritten scores	94.25%	78.72%	73.11%
Printed scores	98.73%	81.15%	79.97%

Table: Results of the music symbols extraction algorithm using both printed and handwritten scores.

Recognition Process[6].

- NN, k-NN and SVM methods: 20×20 pixels then converted to a vector of 400 binary values.

[6] "Metric Learning for Music Symbols Recognition", A. Rebelo, J. Tkaczuk, R. Sousa and J. S. Cardoso, in *In Proceedings of 10th International Conference on Machine Learning and Applications*, 2011.

Recognition Process[6].

- NN, k-NN and SVM methods: 20×20 pixels then converted to a vector of 400 binary values.
- 380 images from 18 perfect scores; separation of composers, gradual increase of deformations and union of real and printed scores.

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- 380 images from 18 perfect scores; separation of composers, gradual increase of deformations and union of real and printed scores.

Handwritten Music Symbols	Accent	BassClef	Beam	Flat	Natural	Note	NoteFlag	NoteOpen	RestI	RestII	Sharp	Staccatissimo	TrebleClef
Printed Music Symbols	AltoClef	TieSlur	Beam	Flat	Natural	Note	NoteFlag	NoteOpen	RestI	RestII	Sharp	Time	TrebleClef

- Dataset was randomly split into training and test sets: 60% and 40%.
- 4-fold cross validation.

[6] "Metric Learning for Music Symbols Recognition", A. Rebelo, J. Tkaczuk, R. Sousa and J. S. Cardoso, in *In Proceedings of 10th International Conference on Machine Learning and Applications*, 2011.

Feature extraction.

1. the percentage of black pixels in the 20×20 pixels window of the image;
2. the orientation of the symbol;
3. the number of vertical holes;
4. the number of horizontal holes;
5. the compactness (the ratio between volume and connected components area);
6. the number of end points in the object skeleton;
7. the number of intersections in the object skeleton.

(Some) Results.

	Neural Network (%)	k-NN (%)	SVM (%)
99% CI for the Expected performance in percentage: average (standard deviation)	[80 (0.7); 83 (2.5)]	[94. (0.0); 95 (0.3)]	[95 (0.1); 96 (0.5)]

Table: Total number of symbols: 3768. Input data: vector of 400 binary values plus 7 music symbol features.

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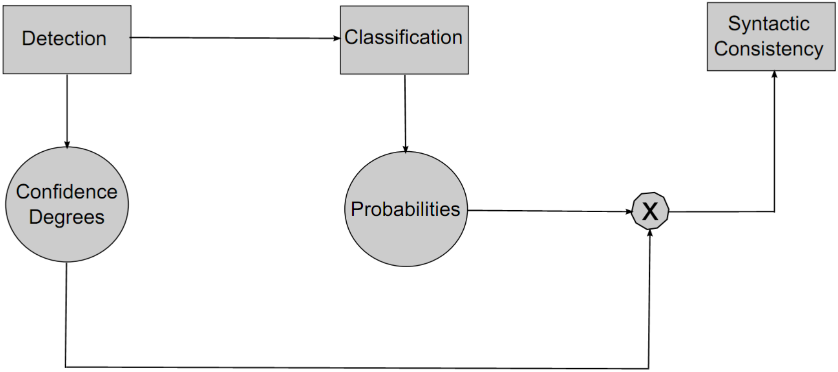
Syntactic consistency process.



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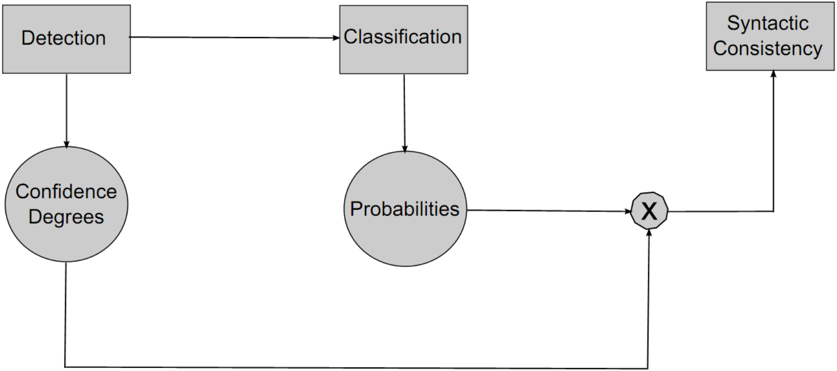

- Missing symbols

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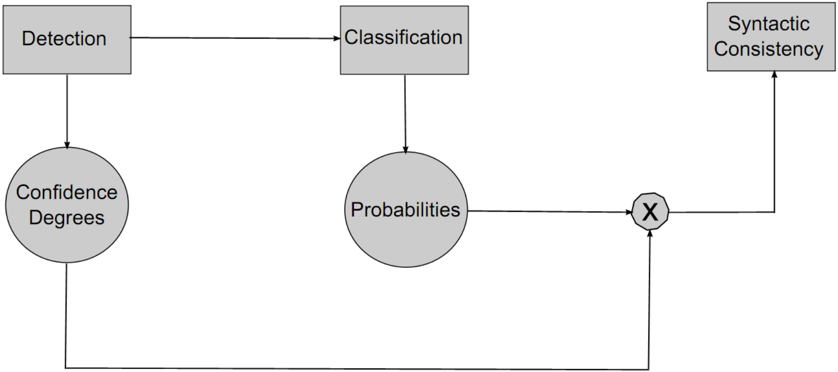

- Missing symbols: the algorithm for music symbols detection is executed more than once until there are no more symbol on the staff, adjusting the several input parameters.

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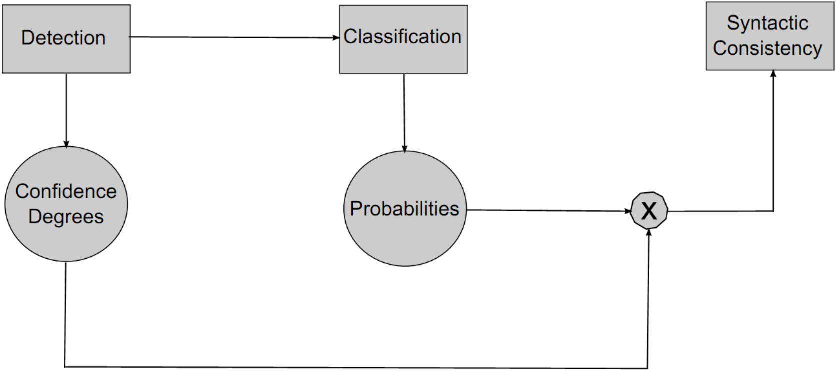

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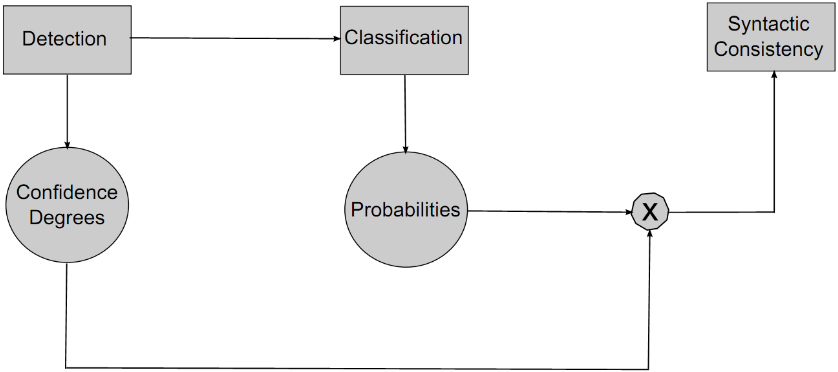

- Missing symbols: the algorithm for music symbols detection is executed more than once until there are no more symbol on the staff, adjusting the several input parameters.
- Symbols confusion and falsely detected symbols: music rules as global constraints.

Confidence degrees.

- As the algorithm detects the various objects it can assign a possible class for each of them with some certainty.
- To measure this certainty favoring the position of the object on the staff we defined a confidence degree.

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Confidence degree: 0.90; 0.05; 0.02; 0.03

Global constraints.

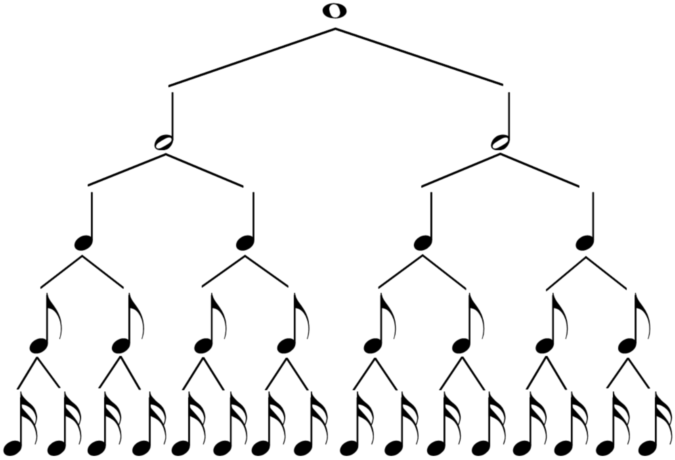
Symbols confusion and falsely detected symbols.

Global constraints.

$$
\begin{aligned}
\max \quad & \sum_{i=1}^{n}\sum_{j=1}^{k} p_{ij}x_{ij} \\
s.t \quad & \begin{array}{l} \sum_{j=1}^{k} x_{ij} \leq 1, i = 1, \ldots, n \\ -N \sum_{j=1}^{k} \sum_{i=1}^{n} \alpha_j x_{ij} = D, i = 1, \ldots, N \\ x_{ij} \in \{0, 1\} \end{array}
\end{aligned} \tag{1}
$$

where p_{ij} is the likelihood of the symbol i to belong to the class j, x_{ij} represents the symbol i from class j, N and D are the top and the bottom numbers in the time signature, respectively, n is the total number of symbols in each staff, k is the total number of classes and α_j is the parameter that represents the relation between the notes associated to each class j.

α: note value.



Measure.

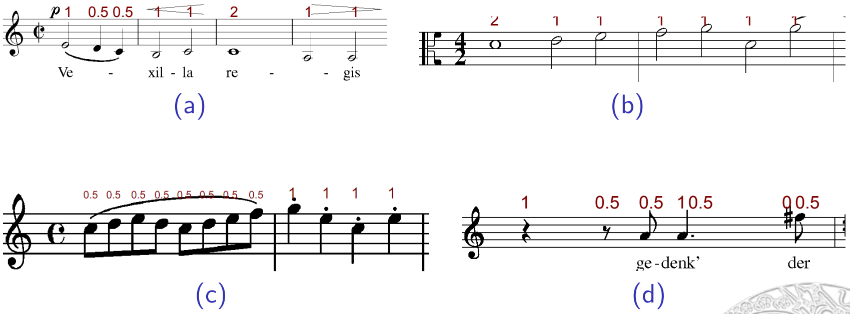


Figure: Examples of measures according to the time signature.

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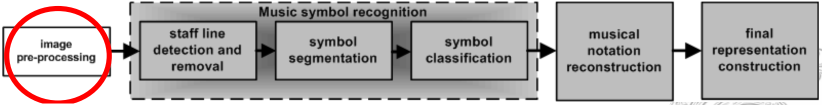

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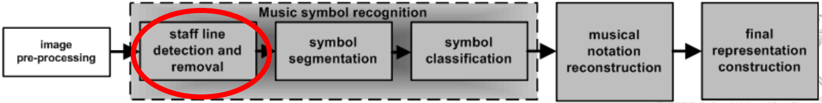

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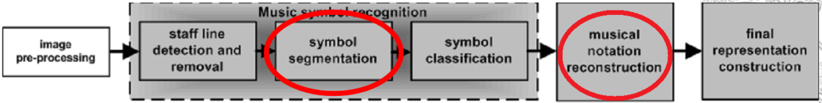

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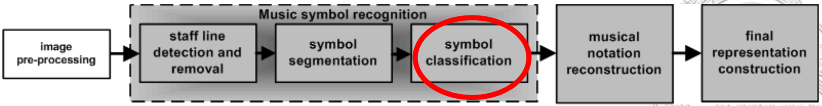

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Conclusion.

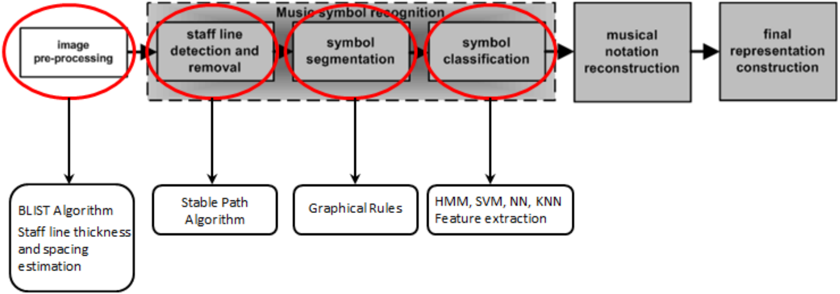

image pre-processing
Music symbol recognition
staff line detection and removal
symbol segmentation
symbol classification
musical notation reconstruction
final representation construction
BLIST Algorithm
Staff line thickness and spacing estimation
Stable Path Algorithm
Graphical Rules
HMM, SVM, NN, KNN
Feature extraction

Future Work.

- Syntactic consistency.
- Evaluation of the entire OMR process.
  Three possible metrics:

$$accuracy = \frac{\#tp + \#tn}{\#tp + \#fp + \#fn + \#tn}$$

$$precision = \frac{\#tp}{\#tp + \#fp}$$

$$recall = \frac{\#tp}{\#tp + \#fn}$$

- Comparison with existing OMR systems.

Publications.

- "Staff Detection with Stable Paths", Jaime S. Cardoso, Artur Capela, Ana Rebelo, Carlos Guedes, Joaquim Pinto da Costa, in *IEEE Transaction on Pattern Analysis and Machine Intelligence*, volume 31, pages 1134–1139, 2009.
- "Robust staffline thickness and distance estimation in binary and gray-level music scores", Jaime S. Cardoso and Ana Rebelo, *In Proceedings of The Twentieth International Conference on Pattern Recognition*, pages 1856–1859, 2010.
- "Optical Recognition of Music Symbols: a comparative study", Ana Rebelo, Artur Capela and Jaime S. Cardoso, in *International Journal on Document Analysis and Recognition*, volume 13, pages 19–31, 2010.
- "Content aware music score pre-processing", Ana Rebelo and Jaime S. Cardoso, in *Proceedings of 16th Portuguese Conference on Pattern Recognition (RECPAD)*, 2010.
- "Music score binarization based on domain knowledge", Telmo Pinto, Ana Rebelo, Gilson Giraldi and Jaime S. Cardoso, in *In Proceedings of 5th Iberian Conference on Pattern Recognition and Image Analysis (IbPRIA)*, 2011.
- "A Method for Music Symbols Extraction based on Musical Rules", Ana Rebelo, Filipe Paszkiewicz, Carlos Guedes, Andre R. S. Marcal, and Jaime S. Cardoso, in *In Bridges: Mathematical Connections in Art, Music, and Science (BRIDGES)*, 2011.
- "Metric Learning for Music Symbols Recognition", Ana Rebelo, Jakub Tkaczuk, Ricardo Sousa and Jaime S. Cardoso, in *In Proceedings of 10th International Conference on Machine Learning and Applications (ICMLA)*, 2011.
- "Music Symbols Extraction Based on Domain Knowledge", Ana Rebelo and Jaime S. Cardoso, in *Proceedings of 17th Portuguese Conference on Pattern Recognition (RECPAD)*, 2011.
- "Optical music recognition - state-of-the-art and open issues for handwritten music scores", Ana Rebelo, Ichiro Fujinaga, Filipe Paszkiewicz, Andre R. S. Marcal, Carlos Guedes, and Jaime S. Cardoso, in *International Journal of Multimedia Information Retrieval*, (SUBMITED) 2012.

Thank you!

Good luck!