Automatic Quality Assessment of Cardiac MRI

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http://kclmmag.org
Cardiac MRI Quality Issues

- Need for high quality images
- Wide range of artefacts
- Manual labeling tedious for large datasets
- Need for automatic quality assessment tools
- Automatic cardiac MR planning

Adopted from Ferreira et al., JCMR, 2013.
Cardiac MR Quality issues

1. **Off-axis (4ch)**
   - Left Ventricular Outflow Tract
   - 5 chamber look

2. **Motion related artefacts (SAX)**
   - Breathing
   - Mis-triggering
   - Arrhythmia

3. **Heart not fully covered**
   - Missing apex
   - Missing basal slice

* Oksuz et al., ISBI 2018
$Oksuz et al., under review
4-Chamber cine Cardiac MRI

- Good 4-chamber CMR image shows all chambers clearly.
- Right and left atrium analysis can be achieved with 4-chamber view.
4-Chamber view planning

- Planned using 2-chamber and short axis images
- An appropriate angle is necessary
Left Ventricular Outflow Tract (LVOT)

- Wrong cardiac planning leads to off-axis acquisitions
- Presence of Left Ventricular Outflow Tract (LVOT)
- Challenges RA and LA analysis
- Automatic LVOT detection can help automatic cardiac planning
Method

**Input:** 2D 4chamber cardiac MR

1. Contrast Normalization
2. Region of Interest Extraction
3. Training a CNN Model

**Output:** LVOT = 0 or 1
ROI Extraction-Template Matching

• Use a separate dataset to generate templates
• Normalize cross correlation for template matching
CNN MODEL

- Similar to Lenet* Model
- 2 Convolutional Layers
- 2 Max Pooling Layers
- Dropout 0.5 after each layer
- ReLU Activation

* LeCun et al., *Proceedings IEEE, 1998*
Dataset and methods of comparison

- 123 Good Quality Image and 123 LVOT Images from UK Biobank*
- 5 temporal frames of each sequence, 615 images for each class
- Stratified 10-fold cross validation
- State of the art classification methods for comparison:
  - K-nearest neighbors
  - Linear SVM
  - Decision Tree
  - Random Forests
  - Adaboost
  - Naïve Bayesian
  - Quadratic Discriminant Analysis

* Petersen et al., *JCMR*, 2016
## Experimental Results

<table>
<thead>
<tr>
<th>Methods</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>K-Nearest Neighbours</td>
<td>0.613</td>
<td>0.604</td>
<td>0.602</td>
</tr>
<tr>
<td>Linear SVM</td>
<td>0.732</td>
<td>0.741</td>
<td>0.736</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.651</td>
<td>0.626</td>
<td>0.619</td>
</tr>
<tr>
<td>Random Forests</td>
<td>0.598</td>
<td>0.613</td>
<td>0.610</td>
</tr>
<tr>
<td>Adaboost</td>
<td>0.718</td>
<td>0.729</td>
<td>0.727</td>
</tr>
<tr>
<td>Naive Bayesian</td>
<td>0.653</td>
<td>0.625</td>
<td>0.637</td>
</tr>
<tr>
<td>Discriminant Analysis</td>
<td>0.669</td>
<td>0.684</td>
<td>0.643</td>
</tr>
<tr>
<td>CNN w.o Augmentation</td>
<td>0.801</td>
<td>0.811</td>
<td>0.781</td>
</tr>
<tr>
<td>CNN</td>
<td>0.826</td>
<td>0.828</td>
<td>0.821</td>
</tr>
</tbody>
</table>

Accuracy = \( \frac{TP + TN}{TP + FP + FN + TN} \)

Precision = \( \frac{TP}{TP + FP} \)

Recall = \( \frac{TP}{TP + FN} \)

* Zhou et al., *CVPR*, 2016
Cardiac MR Quality issues

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* Oksuz et al., ISBI 2018
$Oksuz et al., under review
Cardiac MRI Acquisition

Complete k-space matrix must be obtained for each point in cardiac cycle.

...etc.

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Dataset

- **105 subject** with motion artefacts (Breathing, Mis-triggering, Arrhythmia)
- 53 for Mis-triggering, 23 for Breathing, 24 Arrhythmia, 4 mixed
- **105 Artefact Images, 3360 Good quality Images**
- **DATA IMBALANCE!!!**
Data Imbalance-TODOs

1. Can You Collect More Data?
   • Difficult task in many medical imaging applications

2. Try Resampling Your Dataset
   • You can add copies of instances from the under-represented class.
   • Delete some data from the over-represented class.
   • It is not the best strategy to make use of your data to the fullest.

3. Try to Generate Synthetic Samples
   • Generate synthetic examples that best represent the original data from the under-represented class.
K-space corruption

Frame i
Frame n
Corrupted Frame i

Frame i k-space
Frame n k-space
Frame i corrupted k-space
Synthetic Images

Different corruption levels of k-space

Good Quality | Motion Artefact | K-space corrupted image

HIGH QUALITY → LOW QUALITY
3D CNN MODEL

3D INPUT
2D+time sequence

50X80x80

C1 32@ 3x3x3
C2 64@ 3x3x3
C3 128@ 3x3x3
C4 128@ 3x3x3
C5 128@ 2x2x2
C6 256@ 2x2x2

P1 Pooling 1x2x2
P2 Pooling 1x2x2
P3 Pooling 1x2x2
P4 Pooling 1x2x2

OUTPUT:
Good Quality or Artefact

1024

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## Experimental Results

![Image with mathematical formulas for Precision, Recall, Accuracy, and F1 score](Image)

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<tr>
<th>Methods</th>
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<th>Precision</th>
<th>Recall</th>
<th>F1-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>K-Nearest Neighbours</td>
<td>0.952</td>
<td>0.074</td>
<td>0.268</td>
<td>0.116</td>
</tr>
<tr>
<td>Linear SVM</td>
<td>0.968</td>
<td>0.721</td>
<td>0.385</td>
<td>0.502</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.951</td>
<td>0.250</td>
<td>0.385</td>
<td>0.303</td>
</tr>
<tr>
<td>Random Forests</td>
<td>0.958</td>
<td>0.320</td>
<td>0.315</td>
<td>0.317</td>
</tr>
<tr>
<td>Adaboost</td>
<td>0.960</td>
<td>0.230</td>
<td>0.567</td>
<td>0.327</td>
</tr>
<tr>
<td>Naive Bayesian</td>
<td>0.801</td>
<td>0.527</td>
<td>0.183</td>
<td>0.111</td>
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<tr>
<td>Variance of Laplacian</td>
<td>0.958</td>
<td>0.113</td>
<td>0.161</td>
<td>0.133</td>
</tr>
<tr>
<td>NIQE*</td>
<td>0.958</td>
<td>0.210</td>
<td>0.248</td>
<td>0.227</td>
</tr>
<tr>
<td>CNN with no augmentation</td>
<td>0.968</td>
<td>0.700</td>
<td>0.466</td>
<td>0.560</td>
</tr>
<tr>
<td>CNN with translational augmentation</td>
<td>0.974</td>
<td>0.750</td>
<td>0.600</td>
<td>0.667</td>
</tr>
<tr>
<td>CNN with k-space augmentation</td>
<td>0.977</td>
<td>0.779</td>
<td>0.642</td>
<td>0.704</td>
</tr>
<tr>
<td>CNN with k-space+translational augmentation</td>
<td>0.982</td>
<td>0.809</td>
<td>0.652</td>
<td>0.722</td>
</tr>
</tbody>
</table>

* Mittal et al., *IEEE Signal Processing Letters, 2013*
Conclusions and Future Work

• CNN-based techniques for identifying LVOT presence and motion artefacts
• K-space based corruption for data augmentation
• Neural network with high recall outperforming other state of the art techniques
• Implications for segmentation
• *Plan CMR view-planes automatically*
• *Validate on 100 000 CMR images*
• *Classify each type of artefact separately*
• *Address other CMR quality issues*