Magnifying Spontaneous Facial Micro Expressions for Improved Recognition

Pratikshya Sharma¹, Sonya Coleman¹, Pratheepan Yogarajah¹, Laurence Taggart ², Pradeepa Samarasinghe ³

School of Computing, Engineering & Intelligent Systems¹, School of Nursing², University of Ulster, Northern Ireland
Department of Information Technology ³, Sri Lanka Institute of Information Technology, Sri Lanka

ABSTRACT
We investigate if amplifying micro facial muscle movements as a pre-processing phase, by employing Eulerian Video Magnification (EVM), can boost performance of Local Phase Quantization with Three Orthogonal Planes (LPQ-TOP) to achieve improved facial MER across various datasets. In addition, we examine the rate of increase for recognition to determine if it is uniform across datasets using EVM. Ultimately, we classify the extracted features using Support Vector Machines (SVM). We evaluate and compare the performance with various methods on seven different datasets namely CASME, CAS(ME)¹, CASME2, SMIC-HS, SMIC-NIR and SAMM. The results obtained demonstrate that EVM can enhance LPQ-TOP to achieve improved recognition accuracy.

OBJECTIVE

• To present an extensive analysis to demonstrate the effectiveness of employing EVM with LPQ-TOP on a variety of datasets.
• To provide an insight on the competency of LPQ-TOP as micro facial feature extraction technique.
• Demonstrate the robustness of our approach by adopting more datasets than any other experiment.

METHODOLOGY

• The methodology adopted for our work is demonstrated in Figure 1.
• We have adopted a video magnification method and LPQ-TOP [16][22] feature extraction technique.
• The magnification factor α is set to 26 in equation (1)

\[ (1 + \alpha) s(t) < \frac{1}{B} \]

• LPQ-TOP method is used for extracting features from the magnified frames.
• Calculates four frequency points for each pixel.
• Determines phase information using binary quantizer.
• Builds histogram to represent the resulting codes.
• The final feature vector obtained is trained to a Support Vector Machine (SVM) [4].
• SVM is said to be effective for small datasets with higher dimensions hence, this classification method was chosen for our work as the datasets and method employed match these criteria.

RESULTS

• The result obtained after applying magnification process is shown in Figure 2.
• An enhancement in recognition performance after magnification is evident, however there is an absence of uniformity on the rate of enhancement on all seven datasets.
• An increase of 13.34% in the accuracy has been observed for the CASME2 dataset after introducing magnification which is a significant rise.
• The rate of increase using SMIC-NIR and SMIC-VIS differs by approximately 1% i.e., the method has uniform increase in recognition accuracy on these two SMIC datasets.
• An average increase in recognition accuracy of ~6.14% across all datasets is achieved using the novel framework.
• A significantly improved recognition accuracy of 88.2% is obtained for CASME and is the highest accuracy achieved using the LPQ-TOP with EVM compared to all other datasets.

CONCLUSION

• LPQ-TOP when fused with EVM shows an impressive performance boost on some datasets.
• The results show an impressive average increase of ~6.14% but lacks an orderly increase of recognition accuracy.
• Magnification helped LPQ-TOP to efficiently extract required facial micro features.
• This work has successfully realized performance comparison between LPQ-TOP (with and without EVM) and various other approaches.
• Evidently LPQ-TOP technique is as competent as other hand-crafted methods.
• The goal of performing this work is to provide a novel pipeline for solving three class MER problem.

### Table I. Accuracy % using LPQ-TOP

<table>
<thead>
<tr>
<th>Dataset</th>
<th>No Magnification</th>
<th>With Magnification</th>
<th>% Increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASME</td>
<td>83.45</td>
<td>88.2</td>
<td>6.75</td>
</tr>
<tr>
<td>CASME2</td>
<td>61.16 [18]</td>
<td>74.5</td>
<td>13.34</td>
</tr>
<tr>
<td>CAS(ME)²</td>
<td>63.6</td>
<td>68.5</td>
<td>4.9</td>
</tr>
<tr>
<td>SAMM</td>
<td>70.4</td>
<td>72.07</td>
<td>1.67</td>
</tr>
<tr>
<td>SMIC-VIS</td>
<td>65.6</td>
<td>73.8</td>
<td>8.2</td>
</tr>
<tr>
<td>SMIC-NIR</td>
<td>63.3</td>
<td>70.42</td>
<td>7.12</td>
</tr>
<tr>
<td>SMIC-HS</td>
<td>62.8</td>
<td>65.8</td>
<td>3.0</td>
</tr>
</tbody>
</table>

### Table II. Accuracy % comparison for CASME, CASME2, CAS(ME)², SAMM & SMIC

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Our Work</th>
<th>Other Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>LPQ-TOP + mag</td>
<td>88.2</td>
<td>80.2 MIMPTR [26]</td>
</tr>
<tr>
<td>LPQ-TOP</td>
<td>74.5</td>
<td>78.14 HIGO + mag [27]</td>
</tr>
<tr>
<td>SMIC-VIS</td>
<td>73.8</td>
<td>63.97 HOG + mag [27]</td>
</tr>
<tr>
<td>SMIC-NIR</td>
<td>70.42</td>
<td>60.73 LBP-TOP + mag [27]</td>
</tr>
<tr>
<td>SMIC-HS</td>
<td>65.8</td>
<td>64.07 NMP [31]</td>
</tr>
<tr>
<td>SAMM</td>
<td>72.07</td>
<td>70.18 CNN [32]</td>
</tr>
<tr>
<td>SMIC-VIS</td>
<td>73.8</td>
<td>81.69 HIGO + mag [27]</td>
</tr>
<tr>
<td>SMIC-NIR</td>
<td>70.42</td>
<td>77.46 HOG + mag [27]</td>
</tr>
<tr>
<td>SMIC-HS</td>
<td>65.8</td>
<td>64.79 LBP-TOP + mag [27]</td>
</tr>
<tr>
<td>SMIC-ME²</td>
<td>63.97</td>
<td>67.61 HOG + mag [27]</td>
</tr>
<tr>
<td>SMIC-HS</td>
<td>65.8</td>
<td>68.29 HOG + mag [27]</td>
</tr>
<tr>
<td>SAMM</td>
<td>72.07</td>
<td>61.59 HOG + mag [27]</td>
</tr>
<tr>
<td>SMIC-VIS</td>
<td>73.8</td>
<td>60.37 LBP-TOP + mag [27]</td>
</tr>
</tbody>
</table>

Fig 1. Micro expression recognition framework

Fig 2. Happy Expression[25], before(left) and after(right) magnification. (©Xiaolan Fu)
REFERENCES


