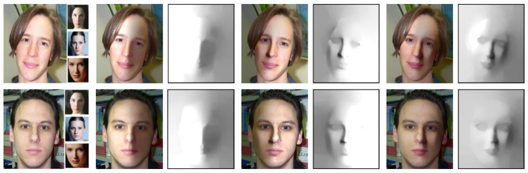

Fig.1 Face relighting with GNN illum. maps

Fig.2 Lowlight image enhancement with GNN illum. maps

Qualitative Experiments: 1) We have made comparison with assorted editing tasks, including face relighting (FR), face swapping (FS), transfiguring (TF) and lowlight image enhancement (LIE). Note that all the related methods were designed for a specific task, while our GNN-based system is flexible to achieve multiple editing effects and obtain the state-of-the-art performance. Since many related methods have not released the source code, we choose some of typical results for comparison, and the experiments do illustrate the superiority of our GNN-based system. In fact, we have only shown parts of the results in this submission due to the page limitation, we would try our best to add more evaluation in the revised version, such as Fig.1-Fig.3.

2) Illumination maps are visualized: Fig.1 shows the FR of male/female with three different references, and the produced results and illumination maps demonstrate the consistency; Fig.2 shows the LIE of Img1 to Img6 (from left to right), which indicate the effectiveness of our GNN method to capture the illumination feature in different scenes.

Fig.3 Image quality assessment of FR and TF by GMSD.

	Img1	Img2	Img3	Img4	Img5	Img6
CVC	6.54	6.28	6.38	6.75	4.27	5.16
LIME	**7.67**	7.43	7.53	**7.65**	5.79	7.23
Ours	7.48	**7.47**	**7.55**	**7.65**	**6.04**	**7.71**

Table1 Image quality assessment of LIE by discrete entropy.

Quantitative Experiments: 1) For FR, FS and TF, we made a small scale user study with 10 volunteers (5 males and 5 females) for the results in the submission, and the GNN results have a higher rank score than the other methods; a larger scale user study for more results would be performed in our journal paper. Furthermore, we used some metric of image quality assessment to for objective evaluation. In objective evaluation of FS and TF, we used gradient magnitude similarity deviation (GMSD) to measure the visual similarity between the target and output pairs (shown in Fig.3), where GMSD1<GMSD2 indicates that our method has better visual consistency than Korshunova's for FS. The results also indicate that our method is competitive to the Shlizerman's and Nirkin's, and obtains better visual consistency.

2) For LIE, Table1 shows the comparison between CVC, LIME and ours by discrete entropy (DE), where a higher value of DE indicates that the image has richer details. The objective comparison indicates that our method is superior to CVC and competitive to the state-of-the-art LIME.

Originality: 1) The GNN model of Scarselli et al. (2009) was originally designed for classification or regression under a supervised learning scheme. This paper further extend and explore GNN in two aspects. **Firstly**, we mathematically distinguish and analyze two intrinsic diffusion properties of GNN, i.e. filtering and propagation, and propose a GNN where guided map and node weight determine the diffusion type; the kernel of graph Laplacian controls the diffusion pattern. Then, we use the GNN to unify many significant CV operations from different fields, like Farbman's optimization-based filter and Liu's PDE-based LTD model. **Secondly**, we generalizes the formulation of Scarselli's GNN (2009) from data classification/regression to visual data manipulation. Since the diffusion type and pattern of GNN can be controlled by our framework, we propose a new kernel structure Eq.(12) with guided feature to construct filtering and propagation operations for QIA, and a three layer GNN-QIA system is built to achieve multi-task editing.

2) This paper focuses on the analysis of different diffusion type and pattern of GNN, and we unifies many significant filtering and propagation operations. Based on the work of this submission, more detailed theoretical analysis of the kernel L would be studied in a much longer journal paper. In fact, the effectiveness of the kernel L for a given task can also be analyzed and optimized via the illumination map, as shown in Fig.1, Fig.2, Fig.4.

Technical Details:1) Fig.4 visualizes workflow of GNN, where QIA-GNN-L1 acts as filtering operation to achieve quotient feature extraction, QIA-GNN-L2 acts as propagation operation to propagate and adjust the feature, QIA-GNN-L3 combines illumination map and image layers to obtain the final output.

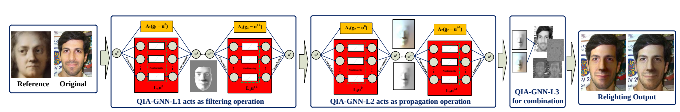

Fig.4 Visualize the illum. map in each GNN-layer for relighting.

2) For FR in Fig.4, if we perform QIA only for the luminance channel of the inputs, we obtain the left output; if we perform QIA for all the RGB channels, we obtain the right output with color transfer.