Improving Phase-Based Motion Magnification algorithm performances by incorporating it as a prior in video inverse problem

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Motivation:

Phase-based motion magnification was introduced few years ago as a technique to manipulate sub-pixel movements in video based on the analysis of motion in complex-value image pyramid [1]. Phase variations of the coefficients of a complex-valued steerable pyramid over time correspond to motion and can be temporally processed and amplified to reveal imperceptible motions, or attenuated to remove distracting changes. In this approach to motion magnification, the motion is not explicitly estimated, but rather magnify by amplifying temporal intensity changes at fixed position.

Phase-based motion magnification is post-processing algorithm, where the motion in a specific temporal frequencies band is amplified. The frequencies band can be chosen based on a known prior knowledge. For example, in cardiac gated MRI acquisition most of the motion is concentrated around heart rate frequency. We speculate that incorporating this prior knowledge into the video inverse problem will improve the motion magnification performances.

Related work:

Motion magnification algorithms are based on the Eulerian and Lagrangian perspectives for flow field. In the Eulerian [2] perspective the motion is not explicitly estimated, but rather magnified by amplifying temporal intensity changes at fixed positions. On the other hand, in the Lagrangian [3] perspective the motion is explicitly estimated over time (optical flow). While the first generation of motion magnification algorithms were based on hand crafted filters, lately learning based approaches [4] have been presented, which learn the spatial decomposition filter directly from examples using deep convolutional neural networks (CNN).

These are pure post-processing algorithms, which does not consider any prior knowledge about the motion we try to reveal. Here we suggest incorporating the prior knowledge about the motion of interest into the video inverse problem to achieved better magnification results.

Project Overview:

Our goal is to test if incorporating prior motion knowledge in the video inverse problem will improve the output of Phase-based motion magnification algorithm, from the perspective of SNR and motion artifacts.

Our objective function defined as follow:

$$\underset{\{\mathbf{x}\}}{\text{minimize}} \quad \underbrace{\frac{1}{2}\|\mathbf{A}\mathbf{x}-\mathbf{b}\|_2^2}_{\text{data fidelity term}} + \underbrace{\lambda\Psi(\mathbf{x})}_{\text{regularizer}} .$$

Where our data fidelity term composed of:

A – Image formation model.
b – original video.
x – amplify video

And the regularizer is the Phase-based motion magnification algorithm, which amplify and constrains (based on prior knowledge) the temporal motion in the estimated amplify video. To better understand why this approach might make sense, we can adopt the Half-quadratic Splitting method to minimize the objective function.

For this method:

$$\mathbf{x} \leftarrow \mathbf{prox}_{f,\rho}(\mathbf{z}) = \underset{\{\mathbf{x}\}}{\arg\min}\ L_\rho(\mathbf{x},\mathbf{z}) = \underset{\{\mathbf{x}\}}{\arg\min}\ f(\mathbf{x}) + \frac{\rho}{2}\|\mathbf{Dx}-\mathbf{z}\|_2^2,$$
$$\mathbf{z} \leftarrow \mathbf{prox}_{g,\rho}(\mathbf{Dx}) = \underset{\{\mathbf{z}\}}{\arg\min}\ L_\rho(\mathbf{x},\mathbf{z}) = \underset{\{\mathbf{z}\}}{\arg\min}\ g(\mathbf{z}) + \frac{\rho}{2}\|\mathbf{Dx}-\mathbf{z}\|_2^2.$$

In our case D is the identity matrix. The z update term can be written as follow:

$$\underset{\{\mathbf{z}\}}{\arg\min}\ \Psi(\mathbf{z}) + \frac{\rho}{2\lambda}\|\mathbf{x}-\mathbf{z}\|_2^2.$$

And as we saw in the class, this equation describes a denoising problem.

From a slightly different perspective, Phase-based motion magnification can be viewed as a denoiser, where the SNR is increased by magnifying the desired known signal (prior) instead of decreasing the level of noise. As a result, we suggest incorporating the prior (Phase-based motion magnification algorithm) as our proximal operator implementing the z-update.

The suggest experiments\pipeline is as follow:

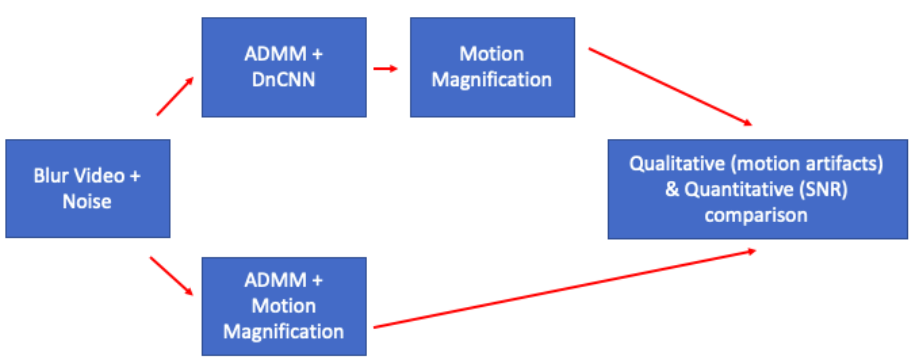

Figure 1 suggested pipeline

The performances of the suggested method will be tested for different level of noise, and for different values of Rho. In addition, we will use DnCNN [5] as a denoiser for the alternative approach (figure 1).

Milestones & Timeline:

- Week 1 – Implementation and incorporation of phase-based motion magnification and ADMM.
- Week 2 – Getting a dataset and testing the algorithm.
- Week 3 – Project presentation and final report writing.

References:

[1] Wadhwa, N., Rubinstein, M., Durand, F., Freeman, W.T.: Phase-based video motion processing. ACM Trans. Graph. (SIGGRAPH) 32(4), 80 (2013)
[2] Liu, C., Torralba, A., Freeman, W.T., Durand, F., Adelson, E.H.: Motion magnification. ACM Trans. Graph. (SIGGRAPH) 24(3), 519–526 (2005)
[3] Wu, H.Y., Rubinstein, M., Shih, E., Guttag, J., Durand, F., Freeman, W.: Eulerian video magnification for revealing subtle changes in the world. ACM Trans. Graph. (SIGGRAPH) 31(4), 65–8 (2012
[4] Oh TH. et al. (2018) Learning-Based Video Motion Magnification. In: Ferrari V., Hebert M., Sminchisescu C., Weiss Y. (eds) Computer Vision – ECCV 2018. ECCV 2018. Lecture Notes in Computer Science, vol 11208. Springer, Cham. https://doi.org/10.1007/978-3-030-01225-0_39
[5] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a Gaussian Denoiser: Residual learning of deep CNN for image denoising," IEEE Trans. Image Process., vol. 26, no. 7, pp. 3142–3155, Jul. 2017.