# On connections between Amplitude Flow and Error Reduction for phase retrieval 

Oleh Melnyk<br>Helmholtz Center Munich,<br>TU Munich<br>oleh.melnyk@tum.de


#### Abstract

In this paper, we consider two iterative algorithms for the phase retrieval problem: the well-known Error Reduction method and the Amplitude Flow algorithm, which performs minimization of the amplitude-based squared loss via the gradient descent. We show that Error Reduction can be interpreted as a quasi-Newton method applied to minimize the same amplitude-based squared loss, which allows to establish its convergence properties. Moreover, we show that for a class of measurement scenarios two methods have the same computational complexity and sometimes even coincide.


## I. Introduction

The problem of phaseless recovery considers the reconstruction of an unknown $x \in \mathbb{C}^{d}$ from a quadratic measurements of the form

$$
\begin{equation*}
y_{j}=\left|(A x)_{j}\right|^{2}+n_{j}, \quad j \in[m] \tag{1}
\end{equation*}
$$

with $A \in \mathbb{C}^{m \times d}, m>d$ denoting the measurement matrix, $n$ - the noise and $[m]:=\{1, \ldots, m\}$. It has many application in the fields of crystallography [1], noncrystalline materials [2], [3], [4] and optical imaging [5].

One of the popular approaches to the recovery of $x$ is the Error Reduction (ER) method [6], [7], [8]. It poses the phase retrieval problem as a problem of finding $A x$, which belongs to the intersection of two sets

$$
\begin{aligned}
\mathcal{M} & :=\left\{u \in \mathbb{C}^{m}:\left|u_{j}\right|^{2}=y_{j}, j \in[m]\right\}, \\
\operatorname{im}(A) & :=\left\{u \in \mathbb{C}^{m}: u=A z \text { for some } z \in \mathbb{C}^{d}\right\}
\end{aligned}
$$

Starting with a guess $z^{0} \in \mathbb{C}^{d}$, ER constructs the initial iterate $u^{0}=A z^{0}$ and then proceeds by consequently projecting $u^{t}$ onto $\mathcal{M}$ and $\operatorname{im}(A)$, so that $u^{t+1}=P_{\operatorname{im}(A)} P_{\mathcal{M}} u^{t}, t \geq 0$, where $P$ denotes the projection operator. Note, that set $\mathcal{M}$ is non-convex and, thus, convergence of the algorithm is not guaranteed theoretically. The iterations are continued until the algorithm finds a fixed point $u^{t+1}=u^{t}$ and an estimate $z^{t}$ corresponding to the least squares solution $u^{t}=A z^{t}$ is returned. When iterations of ER are rewritten with respect to $z^{t}$, it grants the following updates

$$
\begin{equation*}
z^{t+1}=A^{\dagger} \operatorname{diag}\left(\frac{\sqrt{y}}{\left|A z^{t}\right|}\right) A z^{t}, \quad t \geq 0 \tag{ER}
\end{equation*}
$$

where $\operatorname{diag}(u)$ denotes diagonal matrix with vector $u$ on main diagonal, $A^{\dagger}$ is the Moore-Penrose inverse, and the division is performed entrywise. We note that the case $\left(A z^{t}\right)_{j}=0$ for some $j \in[m]$ is special, since there are multiple possible projections on set $\mathcal{M}$. In such a scenario, 0 is commonly mapped to $e^{i \varphi} \sqrt{y_{j}}$ with $\varphi \in[0,2 \pi)$ either some fixed or randomly chosen value. In this paper we map 0 to $0-$ an average value of all possible projections, which corresponds to setting the fraction $\left(A z^{t}\right)_{j} /\left|\left(A z^{t}\right)_{j}\right|$ as zero.

Another popular algorithm is Amplitude Flow (AF) [9], [10], [11], [12], which solves the phase retrieval problem by minimizing the
amplitude-based squared loss

$$
L_{2}(z):=\sum_{j=1}^{m}\left(|A z|-\sqrt{y_{j}}\right)^{2}
$$

via gradient descent. The generalized gradient of $L_{2}$ is given by

$$
\nabla L_{2}(z)=A^{*} \operatorname{diag}\left(1-\frac{\sqrt{y}}{|A z|}\right) A z
$$

with $A^{*}$ denoting conjugate transpose of $A$. Then, starting with an initial guess $z^{0}$, the iterates of AF are generated by

$$
\begin{equation*}
z^{t+1}=z^{t}-\mu \nabla L_{2}\left(z^{t}\right), \quad t \geq 0 \tag{AF}
\end{equation*}
$$

and algorithm terminates, once a fixed (critical) point $z^{t+1}=z^{t}$ is reached. When the learning rate $\mu$ is chosen to be the squared inverse of the spectral norm $\|A\|^{-2}$, AF has a guaranteed convergence rate of $\mathcal{O}\left(t^{-1 / 2}\right)$.

## II. Main Results

Our two main results show that the two algorithms ER and AF are related and have the same sets of fixed points provided the measurement matrices are non-singular.
Theorem II.1. Let $\operatorname{rank}(A)=d$. Then, ER has convergence rate of $\mathcal{O}\left(t^{-1 / 2}\right)$.
Theorem II.2. Let $\operatorname{rank}(A)=d$. Then, $z \in \mathbb{C}^{d}$ is a fixed point of $E R$ if and only if $z$ is the fixed point of $A F$.

At the core of our results is the following lemma.
Lemma II.3. Let $\operatorname{rank}(A)=d$. Then, iterations of $E R$ are quasiNewton iterations given by

$$
z^{t+1}=z^{t}-\left(A^{*} A\right)^{-1} \nabla L_{2}\left(z^{t}\right), \quad t \geq 0
$$

From these results it may seem that two algorithms are comparable. However, a single iteration of ER requires computing the pseudoinverse, which is considerably slower than AF. The next corollary shows, that this difference is less significant when the columns of $A$ are orthogonal and, in fact, the two algorithms are equivalent.
Corollary II.4. Let $A^{*} A=\operatorname{diag}(v)$ for some $v \in \mathbb{R}^{d}, v_{j}>$ $0, j \in[d]$. Then, ER has the same computational complexity as $A F$. Furthermore, if $v_{j}=c, c>0$ for all $j \in[m]$, two algorithms coincide.

An important example where the conditions of Corollary II. 4 are satisfied is ptychography [13], [14], [15], [16], where $A$ represents a discrete Short-time Fourier transform.

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