

# Convergent Tree-Reweighted Message Passing for Energy Minimization

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**Abstract**—Algorithms for discrete energy minimization are of fundamental importance in computer vision. In this paper, we focus on the recent technique proposed by Wainwright et al. [33]—tree-reweighted max-product message passing (TRW). It was inspired by the problem of maximizing a lower bound on the energy. However, the algorithm is not guaranteed to increase this bound—it may actually go down. In addition, TRW does not always converge. We develop a modification of this algorithm which we call *sequential tree-reweighted message passing*. Its main property is that the bound is guaranteed not to decrease. We also give a *weak tree agreement* condition which characterizes local maxima of the bound with respect to TRW algorithms. We prove that our algorithm has a limit point that achieves weak tree agreement. Finally, we show that, our algorithm requires half as much memory as traditional message passing approaches. Experimental results demonstrate that on certain synthetic and real problems, our algorithm outperforms both the ordinary belief propagation and tree-reweighted algorithm in [33]. In addition, on stereo problems with Potts interactions, we obtain a lower energy than graph cuts.

**Index Terms**—Energy minimization, graph algorithms, message passing, belief propagation, early vision, Markov random fields, stereo.

## 1 INTRODUCTION

MANY early vision problems can be naturally formulated in terms of energy minimization, where the energy function has the following form:

$$E(\mathbf{x} | \theta) = \theta_{const} + \sum_{s \in \mathcal{V}} \theta_s(x_s) + \sum_{(s,t) \in \mathcal{E}} \theta_{st}(x_s, x_t). \quad (1)$$

Set  $\mathcal{V}$  usually corresponds to pixels,  $x_s$  denotes the label of pixel  $s \in \mathcal{V}$  which must belong to some finite set. For motion or stereo, the labels are disparities, while, for image restoration, they represent intensities.  $\theta$  defines parameters of the energy:  $\theta_s(\cdot)$  is a unary data penalty function and  $\theta_{st}(\cdot, \cdot)$  is a pairwise interaction potential. This energy is often derived in the context of Markov Random Fields [8]: A minimum of  $E$  corresponds to a *maximum a posteriori* (MAP) labeling  $\mathbf{x}$ .

In general, minimizing  $E$  is an NP-hard problem, so researchers have focused on approximate minimization algorithms. The two most well-known techniques are graph cuts and belief propagation. The former one was introduced in the 1990s [3], [9], [10], [15] and showed a major improvement over previously used simulated annealing [8]. To our knowledge, graph cuts are currently considered to be the most accurate minimization algorithm for energy functions arising in many vision applications, e.g., stereo [3], [14], image restoration [3], image segmentation [2], texture synthesis [19]. In fact, for some functions, it finds a global minimum.

However, graph cuts can be applied only to a limited class of energy functions [3], [10], [15]. If a function falls

outside this class, then one has to use other techniques such as max-product belief propagation (BP) [6], [22], [27], [35]. BP can be applied to any function of the form as in (1), but it has some drawbacks. First, it usually finds a solution with higher energy than graph cuts (in cases when graph cuts can be applied) [28]. Second, BP does not always converge—it often goes into a loop.

### 1.1 Tree-Reweighted Message Passing

Recently, Wainwright et al. [33] introduced a new algorithm for energy minimization called *max-product tree-reweighted message passing* (TRW). We believe that it may become a serious rival to both graph cuts and BP. As can BP, TRW can be applied to any function of the form as in (1). In addition, in this paper, we show that, for stereo problems with Potts interactions TRW obtains a lower energy than both graph cuts and BP. The improvement over graph cuts is marginal and probably would not be a factor for the stereo problem—both algorithms find solutions whose energy is very close to the global minimum. However, it shows the potential of TRW; the difference may become significant for more difficult functions.

Wainwright et al. [33] gave two versions of the TRW algorithm which differ in the schedule of passing messages. These algorithms were inspired by the idea of maximizing a concave lower bound on the energy and have the following property: If their fixed point satisfies a certain condition (“tree agreement”), then it is guaranteed to give a MAP solution (i.e., a global minimum of the energy).

However, TRW algorithms in [33] cannot be viewed as algorithms for direct maximization of the bound. Indeed, in our experiments, we observed that sometimes they decrease it. Also, the algorithms do not always converge; when it happens, the value of the bound often goes into a loop.

Our main contribution is as follows: We show how to modify TRW algorithms so that the value of the bound is

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Manuscript received 21 Feb. 2005; revised 10 Feb. 2006; accepted 28 Feb. 2006; published online 11 Aug. 2006.

Recommended for acceptance by B.J. Frey.

For information on obtaining reprints of this article, please send e-mail to: tpami@computer.org, and reference IEEECS Log Number TPAMI-0097-0205.

guaranteed not to decrease. Thus, we are guaranteed to find at least a “local” maximum of the bound. The word “local” is in quotes since, for concave functions, all local maxima are global if the standard metric space topology is used. Here, we use a weaker topology: Our maxima are local with respect to the TRW algorithms. We formulate the *weak tree agreement* condition (WTA) which gives a precise characterization of such maxima. We prove that our algorithm has a subsequence converging to a vector satisfying WTA.

An interesting question is whether WTA always gives a global maximum of the bound. We show that this is not the case by providing a counterexample. Note that this is different from *sum-product* tree-reweighted message passing [31]: In the latter case, a fixed point of TRW is guaranteed to be the global maximum of the lower bound on the negative log partition function.

TRW algorithms require some choice of trees covering the graph. If the trees have a special structure (namely, chains which are *monotonic* with respect to some ordering on the graph—see Section 3.4), then our algorithm reduces to the message-passing algorithm of Wainwright et al. [33], but with a significant distinction: We update messages in a specific *sequential* order rather than in parallel. In the context of ordinary BP, it was observed experimentally that sequential updates are superior to parallel updates [28], although convergence is still not guaranteed. We give a theoretical justification of sequential updates in the case of tree-reweighted algorithms.

Our sequential schedule has an additional advantage: We show that it can be implemented using half as much space as traditional message passing approaches. A similar observation was made in [6] for bipartite graphs and parallel schedule of updating messages. Our technique can be applied to any graph and is a strict generalization of that in [6].

## 1.2 Other Related Work

Tree-reweighted message passing is closely related to a certain *linear programming (LP) relaxation* of the energy function (described in more detail in Section 2.3). This relaxation has been widely studied in the literature in different contexts. Schlesinger [24] applied it to energy functions of the form 1 whose pairwise terms encode hard constraints:  $\theta_{st}(\cdot, \cdot) \in \{0, +\infty\}$ . Koster et al. [17] formulated this LP relaxation for arbitrary functions  $E(\mathbf{x} | \theta)$  (in their terminology, the problem is called *partial constraint satisfaction*). Chekuri et al. [4] used the formulation for functions with *metric* pairwise terms; they proved certain performance guarantees, e.g., two-approximation bound for the *Potts* energy. (Their work extended the approach of Kleinberg and Tardos [11]). Wainwright et al. [33] studied this LP formulation in the context of the TRW algorithm for general energy functions of the form 1. Recently, Komodakis and Tziritis [16] showed that graph cuts (or, more precisely, the expansion move method in [3]) have close links with this LP. Thus, the LP relaxation in [4], [17], [24], [33] plays a very important role in the theory of MRF optimization algorithms.

Several authors developed specialized techniques that try to solve this linear program. Koval and Schlesinger [18], [25] showed how to find a subgradient direction assuming that a certain *arc consistency* condition is violated. (A description of their *augmenting DAG* algorithm can be found in [34]). Another algorithm with the same stopping criterion

(namely, arc consistency) is *max-sum diffusion*.<sup>1</sup> Note that, after some transformations, arc consistency can be shown to be equivalent to the WTA condition formulated in this paper. Thus, the augmenting DAG, max-sum diffusion, and TRW algorithms have similar stopping criteria. In particular, neither technique is guaranteed to solve the LP relaxation exactly, as our counterexample shows. (Another counterexample due to Schlesinger is given in [34]).

## 1.3 Outline

The paper is organized as follows: In Section 2, we introduce our notation and review some results from [33], in particular, the lower bound on the energy function via convex combination of trees and the duality result. In Section 3, we present our new tree-reweighted algorithm (TRW-S), as well as its analysis. We recommend using a special case of the algorithm, namely, TRW-S with *monotonic chains*. A reader who wants to implement this technique can skip Sections 2 and 3 (except for the first three paragraphs of Section 2) and go directly to Section 4. This section gives a summary of the algorithm. Experimental results are described in Section 5. Finally, we give conclusions in Section 6.

## 2 NOTATION AND BACKGROUND

In this paper, we closely follow the notation used in [33]. However, instead of maximizing posterior probability, we minimize an energy function. Therefore, we replace “min” with “max,” “inf” with “sup,” and vice versa.

Let  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$  be an undirected graph with the set of vertices  $\mathcal{V}$  and the set of edges  $\mathcal{E}$ . For each  $s \in \mathcal{V}$ , let  $x_s$  be a variable taking values in some discrete space  $\mathcal{X}_s$ . By concatenating the variables at each node, we obtain a vector  $\mathbf{x}$  with  $n = |\mathcal{V}|$  elements. This vector takes values in the space  $\mathcal{X} = \mathcal{X}_1 \times \mathcal{X}_2 \times \dots \times \mathcal{X}_n$ . Unless noted otherwise, symbols  $s$  and  $t$  will denote nodes in  $\mathcal{V}$ ,  $(s, t)$  is an edge in  $\mathcal{E}$ , and  $j$  and  $k$  are values in  $\mathcal{X}_s$  and  $\mathcal{X}_t$ , respectively.

As stated in the previous section, our goal is minimizing the function  $E(\mathbf{x} | \theta)$  (1) defined by parameter  $\theta$ . This parameter is specified by constant term  $\theta_{const}$ , unary terms  $\theta_s(j)$ , and pairwise terms  $\theta_{st}(j, k)$ . It is convenient to denote the last two terms as  $\theta_{s;j}$  and  $\theta_{st;jk}$ , respectively. Then,  $\theta$  can be viewed as a vector  $\theta = \{\theta_\alpha | \alpha \in \mathcal{I}\} \in \mathbb{R}^d$ , where the index set  $\mathcal{I}$  is

$$\mathcal{I} = \{const\} \cup \{(s; j)\} \cup \{(st; jk)\}.$$

Note that  $(st; jk) \equiv (ts; kj)$ , so  $\theta_{st;jk}$  and  $\theta_{ts;kj}$  are the same element. We will use notation  $\theta_s$  to denote a vector of size  $|\mathcal{X}_s|$  and  $\theta_{st}$  to denote a vector of size  $|\mathcal{X}_s \times \mathcal{X}_t|$ .

It is convenient to express  $E(\mathbf{x} | \theta)$  as the Euclidean product of two vectors depending on  $\theta$  and  $\mathbf{x}$ . Of course, we cannot write it as  $\langle \theta, \mathbf{x} \rangle$  since  $\theta$  and  $\mathbf{x}$  belong to different spaces. However, we can introduce mapping  $\phi : \mathcal{X} \rightarrow \mathbb{R}^d$  so that

$$E(\mathbf{x} | \theta) = \langle \theta, \phi(\mathbf{x}) \rangle = \sum_{\alpha \in \mathcal{I}} \theta_\alpha \phi_\alpha(\mathbf{x}).$$

Mapping  $\phi$ , called the *canonical overcomplete representation* [30], [32], consists of the following functions  $\phi_\alpha : \mathcal{X} \rightarrow \mathbb{R}$ :

1. The max-sum diffusion algorithm was developed independently by Kovalovsky and Koval in 1975 and by B. Flach in 1998. Neither of the works was published. We learned about this method from [34].

$$\begin{aligned}\phi_{const}(\mathbf{x}) &= 1, \\ \phi_{s;j}(\mathbf{x}) &= [x_s = j], \\ \phi_{st;jk}(\mathbf{x}) &= [x_s = j, x_t = k],\end{aligned}$$

where  $[\cdot]$  is one if its argument is true and zero otherwise.

Let us introduce another notation which we will use extensively throughout the paper. Functions  $\Phi, \Phi_{s;j}, \Phi_{st;jk} : \mathbb{R}^d \rightarrow \mathbb{R}$  give information about the minimum values of the energy under different constraints:

$$\begin{aligned}\Phi(\theta) &= \min_{\mathbf{x} \in \mathcal{X}} E(\mathbf{x} | \theta) \\ \Phi_{s;j}(\theta) &= \min_{\mathbf{x} \in \mathcal{X}, x_s = j} E(\mathbf{x} | \theta) \\ \Phi_{st;jk}(\theta) &= \min_{\mathbf{x} \in \mathcal{X}, x_s = j, x_t = k} E(\mathbf{x} | \theta).\end{aligned}$$

Values  $\Phi_{s;j}(\theta)$  and  $\Phi_{st;jk}(\theta)$  are called *min-marginals* for node  $s$  and edge  $(s, t)$ , respectively.

## 2.1 Max-Product Belief Propagation

The key subroutine of tree-reweighted message passing algorithms is *max-product belief propagation* (BP) of Pearl [22]. BP is an algorithm for approximate minimization of energy  $E(\mathbf{x} | \bar{\theta})$  as in (1); it is exact if the graph is a tree.<sup>2</sup> Let us review how BP works. It maintains a *message*  $M_{st} = \{M_{st;k} | k \in \mathcal{X}_t\}$  for each directed edge  $(s \rightarrow t) \in \mathcal{E}$  which is a vector with  $|\mathcal{X}_t|$  components. We denote  $M = \{M_{st}\}$  to be the vector of all messages.

The basic operation of BP is *passing a message* from node  $s$  to node  $t$  for directed edge  $(s \rightarrow t) \in \mathcal{E}$ . It consists of updating vector  $M_{st}$  as follows:

$$M_{st;k} := \min_{j \in \mathcal{X}_s} \left\{ \left( \bar{\theta}_{s;j} + \sum_{(u \rightarrow s) \in \mathcal{E}, u \neq t} M_{us;j} \right) + \bar{\theta}_{st;jk} \right\} + const_t,$$

where  $const_t$  is a constant independent of  $k$ .<sup>3</sup> We will say that a message for directed edge  $(s \rightarrow t)$  is *valid* if this update does not change  $M_{st}$  (or change it by a constant independent of  $k$ ). The BP algorithm keeps passing messages for edges in some order until convergence, i.e., until all messages are valid.

If the graph contains loops, then, in general, convergence is not guaranteed. In this paper, however, BP is applied only to tree-structured subgraphs. In this case, only two passes are needed to achieve convergence: inward (sending messages from leaves to a root) and outward (sending messages from the root to leaves). Note that any node can serve as a root.

## 2.2 Reparameterization

If two parameter vectors  $\theta$  and  $\bar{\theta}$  define the same energy function (i.e.,  $E(\mathbf{x} | \theta) = E(\mathbf{x} | \bar{\theta})$  for all  $\mathbf{x} \in \mathcal{X}$ ) then  $\theta$  is called a *reparameterization* of  $\bar{\theta}$  [5], [25], [26], [30], [32] (in [25] this notion was called *equivalent transformations*). We will write this as  $\theta \equiv \bar{\theta}$ . Note that this condition does not necessarily imply that  $\theta = \bar{\theta}$  since there are various linear relations among potential functions  $\phi_\alpha$ . Indeed, any

message vector  $M = \{M_{st}\}$  defines reparameterization  $\theta = \bar{\theta}[M]$  of the original parameter vector  $\bar{\theta}$  as follows:

$$\begin{aligned}\theta_t &= \bar{\theta}_t + \sum_{(s \rightarrow t) \in \mathcal{E}} M_{st}, \\ \theta_{st;jk} &= \bar{\theta}_{st;jk} - M_{st;k} - M_{t;s;j}, \\ \theta_{const} &= \bar{\theta}_{const}.\end{aligned}$$

We prove in Appendix B that the opposite is also true: Any reparameterization  $\theta$  of vector  $\bar{\theta}$  can be expressed via messages, up to a *constant parameter vector*.<sup>4</sup>

Reparameterization provides an alternative way of implementing BP algorithm. As discussed in Section 2.1, standard BP stores the original parameter vector  $\bar{\theta}$  and messages  $M$ . Alternatively, we can store the reparameterization  $\theta = \bar{\theta}[M]$ , in which case, the vectors  $\bar{\theta}$  and  $M$  are not needed. It turns out that sending a message from node  $s$  to node  $t$  is equivalent to reparameterizing vectors  $\theta_t$  and  $\theta_{st}$  for node  $t$  and edge  $(s, t)$ , respectively [32]. It can also be shown [32] that a message for directed edge  $(s \rightarrow t)$  is valid iff

$$\min_{j \in \mathcal{X}_s} \{\theta_{s;j} + \theta_{st;jk}\} = const_{st} \quad \forall k \in \mathcal{X}_t. \quad (2)$$

If this condition holds, then sending a message from  $s$  to  $t$  does not change  $\theta_{st}$  and  $\theta_t$  (or change them by a constant independent of  $j$  or  $k$ ). We say that  $\theta$  is in a *normal form* if all messages are valid.

For a tree-structured graph, values  $\theta_{s;j}$  and  $\theta_{st;jk}$  for vector  $\theta$  in a normal form have a particularly simple interpretation [32]—they correspond to min-marginals (up to a constant):

$$\begin{aligned}\Phi_{s;j}(\theta) &= \theta_{s;j} + const_s, & (3a) \\ \Phi_{st;jk}(\theta) &= \{\theta_{s;j} + \theta_{st;jk} + \theta_{t;k}\} + const_{st}. & (3b)\end{aligned}$$

### 2.2.1 Canonical Normal Form

We will say that vector  $\theta$  is in a *canonical normal form* if, in addition to (2), it satisfies the following conditions for all nodes and edges:

$$\begin{aligned}\min_j \theta_{s;j} &= 0, \\ \min_{j,k} \{\theta_{s;j} + \theta_{st;jk} + \theta_{t;k}\} &= 0.\end{aligned}$$

Any vector  $\theta$  in a normal form can be reparameterized into a canonical normal form by subtracting a constant from vectors  $\theta_s$  and  $\theta_{st}$  and adding the same constant to  $\theta_{const}$ . Canonical normal form is quite useful because constants in (2) and (3) can be written down explicitly (see Appendix A).

## 2.3 Linear Programming Relaxation

In general, the problem of minimizing energy of form 1 is NP-hard. Therefore, researchers have focused on approximation algorithms. One of the approaches [4], [17], [24], [33] uses a linear programming (LP) relaxation technique. Let us define the following constraint set:

$$LOCAL(\mathcal{G}) = \left\{ \tau \in \mathbb{R}_+^d \left| \begin{array}{l} \tau_{const} = 1 \\ \sum_{j \in \mathcal{X}_s} \tau_{s;j} = 1 \\ \sum_{j \in \mathcal{X}_s} \tau_{st;jk} = \tau_{t;k} \end{array} \right. \right\}.$$

2. From now on, we will use notation  $\bar{\theta}$  for the original energy function rather than  $\theta$ . The reason for this will be clear in the next section.

3. Throughout the paper, we use notation  $const_t$  or  $const_{st}$  to denote constants independent of  $k$  or  $j$ . These constants may be different in different equations.

4. We have recently learned that a proof of this fact was given by Schlesinger in his lectures (NTUU ‘‘KPI,’’ Kiev). To our knowledge, this proof was not published.

It is easy to check that, for any configuration  $\mathbf{x} \in \mathcal{X}$ , solution vector  $\phi(\mathbf{x})$  belongs to this set. Therefore, the following minimization problem yields a lower bound on  $\Phi(\bar{\theta})$ :

$$\min_{\tau \in \text{LOCAL}(\mathcal{G})} (\bar{\theta}, \tau). \quad (4)$$

As shown in [4], this relaxation has several interesting properties. Here, we mention just one. Suppose that energy function  $E(\mathbf{x} | \theta)$  has *Potts* interaction terms and parameter vector  $\theta$  is nonnegative. Then, by solving this minimization problem and by using randomized technique proposed in [11], we obtain configuration  $\mathbf{x}$  such that the expected value of  $E(\mathbf{x} | \theta)$  is at most twice the optimal value of the energy.

Unfortunately, general linear programming algorithms such as interior point methods are rather slow, and currently, solving (4) is not computationally feasible for large vision problems such as stereo. Specialized techniques exploiting the structure of the problem were developed in [18] and in [33]. Both approaches try to solve a *dual* to (4). First, a lower bound on the energy  $E(\mathbf{x} | \theta)$  is formulated (i.e., a function of dual variables which is always smaller than or equal to the minimum of  $E$ ). The goal then becomes to maximize this bound. In this paper, we will follow the approach in [33] in which the lower bound is formulated via a *convex combination of trees*. This approach is described in the next section.

## 2.4 Convex Combination of Trees

First, we need to introduce some notation. Let  $\mathcal{T}$  be a collection of trees in graph  $\mathcal{G}$  and  $\rho^T$ ,  $T \in \mathcal{T}$ , be some distribution on  $\mathcal{T}$ . Throughout the paper, we assume that each tree has a nonzero probability and each edge in  $\mathcal{E}$  is covered by at least one tree. For a given tree  $T = (\mathcal{V}^T, \mathcal{E}^T)$ , we define a set

$$\mathcal{I}^T = \{\text{const}\} \cup \{(s; j) | s \in \mathcal{V}^T\} \cup \{(st; jk) | (s, t) \in \mathcal{E}^T\}$$

corresponding to those indexes associated with vertices and edges in the tree.

To each tree  $T \in \mathcal{T}$ , we associate an energy parameter  $\theta^T$  that must respect the structure of  $T$ . More precisely, the parameter  $\theta^T$  must belong to the following linear constraint set:

$$\mathcal{A}^T = \{\theta^T \in \mathbb{R}^d | \theta_\alpha^T = 0 \forall \alpha \in \mathcal{I} \setminus \mathcal{I}^T\}.$$

By concatenating all of the tree vectors, we form a larger vector  $\theta = \{\theta^T | T \in \mathcal{T}\}$ , which is an element of  $\mathbb{R}^{d \times |\mathcal{T}|}$ . Vector  $\theta$  must belong to the constraint set

$$\mathcal{A} = \{\theta \in \mathbb{R}^{d \times |\mathcal{T}|} | \theta^T \in \mathcal{A}^T \text{ for all } T \in \mathcal{T}\}.$$

Consider function  $\Phi_\rho : \mathcal{A} \rightarrow \mathbb{R}$ , defined as follows:

$$\Phi_\rho(\theta) = \sum_T \rho^T \Phi(\theta^T) = \sum_T \rho^T \min_{\mathbf{x} \in \mathcal{X}} \langle \theta^T, \phi(\mathbf{x}) \rangle.$$

Wainwright et al. [33] show that, if  $\sum_T \rho^T \theta^T = \bar{\theta}$ , then  $\Phi_\rho(\theta)$  is a lower bound on the optimal value of the energy for vector  $\bar{\theta}$  (this follows from Jensen's inequality). To get the tightest bound, we can consider the following maximization problem:

$$\max_{\theta \in \mathcal{A}, \sum_T \rho^T \theta^T = \bar{\theta}} \Phi_\rho(\theta). \quad (5)$$

$\Phi_\rho$  is a concave function of  $\theta$ ; moreover, the constraints of (5) are linear in  $\theta$ . The following theorem, proven in [33], characterizes the dual to (5).<sup>5</sup>

**Theorem 1.** *Minimization problem (4) is the Lagrangian dual to maximization problem (5). Strong duality holds, so their optimal values coincide.*

A surprising consequence of this theorem is that the optimal value of (5) does not depend on the choice of trees and their probabilities (as long as each edge is covered with nonzero probability).

## 3 NEW TREE-REWEIGHTED MESSAGE PASSING ALGORITHM

In the previous section, we introduced our notation and described previous work. Now, we can concentrate on our contributions.

We start by modifying maximization problem (5). This problem inspired two algorithms in [33]—tree-reweighted message passing with edge-based updates (TRW-E) and with tree-based updates (TRW-T). However, neither algorithm maintains constraint  $\sum_T \rho^T \theta^T = \bar{\theta}$  of (5). Indeed, they perform reparameterizations of the original parameter vector, so this equality may become violated.<sup>6</sup> Let us replace it with the constraint  $\sum_T \rho^T \theta^T \equiv \bar{\theta}$ . Thus, we are now interested in the following maximization problem:

$$\max_{\theta \in \mathcal{A}, \sum_T \rho^T \theta^T = \bar{\theta}} \Phi_\rho(\theta). \quad (6)$$

The following lemma justifies this formulation.

**Lemma 3.1.** *The optimal value of (6) equals the optimal value of (5).*

**Proof.** See Appendix C. The proof involves showing that any reparameterization can be expressed via messages.  $\square$

As shown in [33], the TRW-E and TRW-T algorithms maintain the constraint of (6). Unfortunately, they do not guarantee that the objective function  $\Phi_\rho$  monotonically increases—in our experiments, we have observed that sometimes it goes down. In fact, when the algorithms failed to converge, the value of  $\Phi_\rho(\theta)$  often had gone into a loop. Next, we design a new algorithm with the property that  $\Phi_\rho$  never decreases.

Our algorithm is shown in Fig. 1. It iterates between two steps: 1) reparameterizing vectors  $\theta^T$  and 2) averaging element  $\omega \in \mathcal{V} \cup \mathcal{E}$ . The goal of the reparameterization step is to make sure that the algorithm satisfies the *min-marginal property*:

- *In the beginning of the averaging operation for element  $\omega$ , components of vectors  $\theta^T$  corresponding to  $\omega$  should give correct min-marginals for trees  $T \in \mathcal{T}_\omega$  (3).*

This property will turn out to be crucial in the analysis of the algorithm.

Note that the TRW-E and TRW-T algorithms can also be formulated as combinations of the reparameterization and

<sup>5</sup> Wainwright et al. [33] formulated this theorem for the case when trees in  $\mathcal{T}$  are *spanning*. However, their proof never uses this assumption. In this paper, we do not assume that trees are spanning.

<sup>6</sup> Note that Lemmas 5 and 11 in [33] seem to contain a mistake. Lemma 11, for example, says that the TRW-T algorithm maintains the property  $\sum_T \rho^T \theta^T = \bar{\theta}$ . However, the proof does not take into the account reparameterization step.

0. Initialize  $\theta$  so that  $\theta \in \mathcal{A}$  and  $\sum_T \rho^T \theta^T \equiv \bar{\theta}$ .
  1. Select some order for nodes and edges in  $\mathcal{V} \cup \mathcal{E}$ . For each element  $\omega \in \mathcal{V} \cup \mathcal{E}$  find all trees  $\mathcal{T}_\omega \subseteq \mathcal{T}$  containing  $\omega$ . If there is more than one tree, then do the following:
    - (a) For all trees  $T \in \mathcal{T}_\omega$  reparameterize  $\theta^T$  such that values  $\theta_{s;j}^T$  (if  $\omega = s$  is a node) or  $\theta_{s;j}^T + \theta_{st;jk}^T + \theta_{t;k}^T$  (if  $\omega = (s, t)$  is an edge) give correct min-marginals for tree  $T$  as in formulas (3).
    - (b) “Averaging” operation:
      - If  $\omega = s$  is a node in  $\mathcal{V}$  then
        - Compute  $\tilde{\theta}_s = \frac{1}{\rho_s} \sum_{T \in \mathcal{T}_s} \rho^T \theta_s^T$
        - Set  $\theta_s^T := \tilde{\theta}_s$  for trees  $T \in \mathcal{T}_s$
      - If  $\omega = (s, t)$  is an edge in  $\mathcal{E}$  then
        - Compute  $\tilde{\nu}_{st;jk} = \frac{1}{\rho_{st}} \sum_{T \in \mathcal{T}_{st}} \rho^T (\theta_{s;j}^T + \theta_{st;jk}^T + \theta_{t;k}^T)$
        - Set  $\theta_s^T, \theta_{st}^T, \theta_t^T$  for trees  $T \in \mathcal{T}_{st}$  so that  $\theta_{s;j}^T + \theta_{st;jk}^T + \theta_{t;k}^T = \tilde{\nu}_{st;jk}$
  2. Check whether a stopping criterion is satisfied; if yes, terminate, otherwise go to step 1.

Fig. 1. The sequential tree-reweighted algorithm (TRW-S).  $\rho_s$  is the *node appearance probability*, i.e., the probability that a tree chosen randomly under  $\rho$  contains node  $s$ . Similarly,  $\rho_{st}$  is the *edge appearance probability*.

averaging operations.<sup>7</sup> However, they update vectors  $\theta^T$  in parallel, while we do it sequentially. Therefore, we call our algorithm “sequential tree-reweighted message passing” (TRW-S).

Reparameterization Step 1(a) can be implemented in many different ways. One possibility is to convert vectors  $\theta^T$  to normal forms by running the ordinary max-product BP. However, this would be very expensive if the trees are large. A more efficient technique is discussed in Section 3.4.

### 3.1 Weak Tree Agreement

The algorithm in Fig. 1 does not specify what the stopping criterion is. In this section, we address this issue by giving the *weak tree agreement* condition (WTA). Later, we will show that it characterizes local maxima of the algorithm with respect to function  $\Phi_\rho$ . More precisely, we will prove that the algorithm has a subsequence converging to a vector satisfying the WTA condition. Moreover, if a vector satisfies this condition, then the algorithm will not make any progress, i.e., it will not increase function  $\Phi_\rho$ .

In order to define the WTA condition, it is convenient to introduce some notation. Let  $OPT^T(\theta^T)$  be the set of optimal configurations for parameter  $\theta^T$ . Let  $OPT(\theta)$  be the collection  $\{OPT^T(\theta^T) \mid T \in \mathcal{T}\}$  of the sets of optimal configurations for vectors  $\theta^T$ . It belongs to the set  $(2^{\mathcal{X}})^{|\mathcal{T}|} = 2^{\mathcal{X}} \times \dots \times 2^{\mathcal{X}}$  ( $|\mathcal{T}|$  times). For two collections  $\mathbf{S}, \tilde{\mathbf{S}} \in (2^{\mathcal{X}})^{|\mathcal{T}|}$ , we will write  $\mathbf{S} \subseteq \tilde{\mathbf{S}}$  if  $\mathbf{S}^T \subseteq \tilde{\mathbf{S}}^T$  for every tree  $T$ .

Consider some collection of sets of configurations  $\mathbf{S} = \{\mathbf{S}^T\} \in (2^{\mathcal{X}})^{|\mathcal{T}|}$ . We say that  $\mathbf{S}$  is *consistent* if it satisfies the following three conditions:

1. For every tree  $T$ , set  $\mathbf{S}^T$  is nonempty.
2. If node  $s$  is contained in trees  $T$  and  $T'$ , then, for every configuration  $\mathbf{x} \in \mathbf{S}^T$ , there exists configuration  $\mathbf{x}' \in \mathbf{S}^{T'}$  which agrees with  $\mathbf{x}$  on node  $s$ , i.e.,  $x_s = x'_s$ .

7. The TRW-T algorithm iterates between two phases: 1) running max-product BP for *all* trees and 2) performing averaging operation for *all* nodes and edges. TRW-E is similar, except that, in phase 1, it performs one parallel message update operation for all trees. In general, the TRW-E and TRW-T algorithms do not satisfy the min-marginal property.

3. If edge  $(s, t)$  is contained in trees  $T$  and  $T'$ , then, for every configuration  $\mathbf{x} \in \mathbf{S}^T$ , there exists configuration  $\mathbf{x}' \in \mathbf{S}^{T'}$  which agrees with  $\mathbf{x}$  on nodes  $s$  and  $t$ , i.e.,  $x_s = x'_s, x_t = x'_t$ .

Now, we can define the WTA condition.

**Definition 3.2.** Vector  $\theta = \{\theta^T\} \in \mathcal{A}$  is said to satisfy the *weak tree agreement condition* if there exists collection  $\mathbf{S} \subseteq OPT(\theta)$  which is consistent.

Note that it can be viewed as a generalization of the *tree agreement* condition introduced in [33]: Vectors satisfying the tree agreement also satisfy WTA condition.

Also, note that the WTA condition is different from the *fixed point* condition of TRW algorithms. The latter means that any step of the algorithm does not change vector  $\theta$ . This, in turn, implies that all vectors  $\theta^T$  are in a normal form and  $\theta_\omega^T = \theta_\omega^{T'}$  for every element  $\omega \in \mathcal{V} \cup \mathcal{E}$  and for every pair of trees  $T, T' \in \mathcal{T}_\omega$ . It is easy to see that every fixed point of TRW satisfies the WTA condition, but not the other way around.

### 3.2 Analysis of the Algorithm: Main Theorems

First, we show that similarly to TRW-T algorithm, TRW-S maintains the constraint of (6).

**Lemma 3.3.** The TRW-S algorithm performs reparameterization of the original parameter vector  $\theta$ , i.e., it maintains the property  $\sum_T \rho^T \theta^T \equiv \bar{\theta}$ .

**Proof.** By definition, Step 1(a) performs reparameterizations of tree vectors  $\theta^T$  and, thus, reparameterizations of the sum  $\sum_T \rho^T \theta^T$ . Checking that Step 1(b) is a reparameterization is simple algebra.  $\square$

Next, we analyze the behavior of objective function  $\Phi_\rho$  during the algorithm. To be specific, we assume, for the rest of this section, that, after reparameterization Step 1(a), we have  $\min_j \{\theta_{s;j}^T\} = 0$  (if  $\omega = s$  is a node) or  $\min_{j,k} \{\theta_{s;j}^T + \theta_{st;jk}^T + \theta_{t;k}^T\} = 0$  (if  $\omega = (s, t)$  is an edge). This assumption is not essential, however; the behavior of the algorithm will be the same for any other normalization.

**Theorem 3.4.** 1) After any number of steps, functions  $\Phi$  and  $\Phi_\rho$  do not decrease. 2) If vector  $\theta$  does not satisfy the WTA condition, then, after a finite number of iterations, function  $\Phi_\rho$  will increase. 3) If vector  $\theta$  satisfies the WTA condition with collection  $\mathbf{S}$ , then, after any number of steps, it will still satisfy WTA with the same collection  $\mathbf{S}$ . Function  $\Phi_\rho$  will not change.

A proof of this theorem is given in the next section.

As an immediate consequence of Theorem 3.4, Part 1, we get the following result:

**Corollary 3.5.** If vector  $\theta$  maximizes (6), then  $\theta$  satisfies the WTA condition.

Unfortunately, the converse is not necessarily true, as the example in Appendix D demonstrates.

Finally, we give the convergence theorem. A proof is given in the next section.

**Theorem 3.6.** Let  $\{\theta^{(i)}\}_i$  be an infinite sequence of vectors obtained by applying Step 1 of the TRW-S algorithm. Let  $\{\tilde{\theta}^{(i)}\}_i$  be the reparameterization of this sequence obtained by reparameterizing vectors  $\theta^{(i)}$  into the canonical normal form. Then, there is a subsequence  $\{\tilde{\theta}^{(i(m))}\}_m$  such that

1. it converges to some vector  $\theta^* \in \mathcal{A}$ ,
2. sequence  $\{\Phi_\rho(\tilde{\theta}^{(i)})\}_i$  converges to  $\Phi_\rho(\theta^*)$ , and
3. vector  $\theta^*$  satisfies WTA condition.

Note that, since the algorithm does not specify exactly how we reparameterize vectors  $\theta^{(i)}$ , we cannot claim that sequence  $\{\theta^{(i)}\}_i$  always contains a converging subsequence. As a counterexample, we could choose  $\{\theta^{(i)}\}_i$  so that it is not bounded. Reparameterization  $\{\tilde{\theta}^{(i)}\}_i$  in the theorem was chosen only to make sure that it is bounded.

### 3.3 Analysis of the Algorithm: Proofs

In this section, we prove Theorems 3.4 and 3.6. The most important property of the algorithm, namely, Theorem 3.4, Part 1 (nondecreasing lower bound) is proven in the beginning of the next section. This proof is instrumental for understanding the structure of the algorithm. Other parts of the proof are more technical; the reader may want to skip them and go to Section 3.4.

#### 3.3.1 Proof of Theorem 3.4

All quantities used in the theorem are defined using functions  $E(\cdot | \theta^T)$ . By definition, reparameterization Step 1(a) does not change these functions. Therefore, we do not need to consider these steps, so we only need to analyze the averaging Step 1(b). The following lemma shows the effect of the averaging operation on functions  $\Phi$ .

**Lemma 3.7.** Suppose that the averaging operation for element  $\omega$  transforms vectors  $\theta^T$  to vectors  $\tilde{\theta}^T$ .

- If  $\omega = s$  is a node, then  $\Phi_{s;j}(\tilde{\theta}^T) = \Phi(\theta^T) + \tilde{\theta}_{s;j}$  for every tree  $T \in \mathcal{T}_s$ .
- If  $\omega = (s, t)$  is an edge, then  $\Phi_{st;jk}(\tilde{\theta}^T) = \Phi(\theta^T) + \tilde{\theta}_{s;j} + \tilde{\theta}_{st;jk} + \tilde{\theta}_{t;k}$  for every tree  $T \in \mathcal{T}_{st}$ .

**Proof.** We consider only the case when  $\omega = s$  is a node. The second case is very similar.

Because of our normalization assumption, we have

$$\Phi(\theta^T) = \min_{j \in \mathcal{X}_s} \Phi_{s;j}(\theta^T) = \min_{j \in \mathcal{X}_s} \{\theta_{s;j}^T\} + \text{const}_s = \text{const}_s,$$

where  $\text{const}_s$  is the constant in (3a). Plugging this into (3a), we get  $\Phi_{s;j}(\theta^T) = \Phi(\theta^T) + \theta_{s;j}^T$ .

Vectors  $\theta^T$  and  $\tilde{\theta}^T$  agree on all nodes and edges other than node  $s$ . Thus, they have the same optimal configuration  $\mathbf{x}^j$  under the constraint  $x_s^j = j$ . We can write

$$\begin{aligned} \Phi_{s;j}(\tilde{\theta}^T) &= E(\mathbf{x}^j | \tilde{\theta}^T) = E(\mathbf{x}^j | \theta^T) - \theta_{s;j}^T + \tilde{\theta}_{s;j}^T \\ &= \Phi_{s;j}(\theta^T) - \theta_{s;j}^T + \tilde{\theta}_{s;j}^T = \Phi(\theta^T) + \tilde{\theta}_{s;j}^T. \end{aligned}$$

□

Parts 1) and 3) of Theorem 3.4 are immediate consequences of this lemma. Indeed, for the node averaging operation, for example, we can write

$$\Phi(\tilde{\theta}^T) = \min_{j \in \mathcal{X}_s} \Phi_{s;j}(\tilde{\theta}^T) = \Phi(\theta^T) + \min_{j \in \mathcal{X}_s} \{\tilde{\theta}_{s;j}^T\}. \quad (7)$$

We have  $\theta_s^T \geq 0$ ; inspecting the update rule of Step 1(b), we conclude that  $\tilde{\theta}_s^T \geq 0$  as well. Therefore, the minimum on the RHS is nonnegative, so  $\Phi(\tilde{\theta}^T) \geq \Phi(\theta^T)$  and  $\sum_T \rho^T \Phi(\tilde{\theta}^T) \geq \sum_T \rho^T \Phi(\theta^T)$ . This proves Part 1).

Let us prove Part 3). Suppose that  $\theta$  satisfies WTA with collection  $\mathbf{S} = \{\mathbf{S}^T\}$ . We need to prove that  $\mathbf{S} \subseteq \text{OPT}(\tilde{\theta})$ . We can ignore trees  $T'$  that do not contain node  $s$  since vector  $\theta^{T'}$  and set  $\text{OPT}(\theta^{T'})$  do not change. Let us pick a tree  $T \in \mathcal{T}_s$ . Consider a configuration  $\mathbf{x} \in \mathbf{S}$  and let  $j = x_s$ . Since  $\mathbf{S}$  is consistent, for every tree  $T' \in \mathcal{T}_s$  there exists a configuration  $\mathbf{x}'$  with  $x'_s = j$  that is optimal for  $\theta^{T'}$ . This implies that  $\theta_{s;j}^{T'} = 0$  for every  $T' \in \mathcal{T}_s$ . Therefore, we have  $\tilde{\theta}_{s;j}^T = 0$ .

One consequence of this fact is that the minimum in (7) is zero, so  $\Phi(\tilde{\theta}^T) = \Phi(\theta^T)$ . Also, it means that  $E(\mathbf{x} | \tilde{\theta}) = \Phi(\tilde{\theta}^T)$ , i.e.,  $\mathbf{x}$  is an optimal configuration for vector  $\tilde{\theta}^T$ :  $\mathbf{x} \in \text{OPT}^T(\tilde{\theta}^T)$ . Part 3) is proven.

To prove Part 2), we need the following lemma.

**Lemma 3.8.** Suppose that a complete pass of Step 1 transforms vector  $\theta$  to vector  $\tilde{\theta}$  and  $\Phi_\rho(\theta) = \Phi_\rho(\tilde{\theta})$ . Then,  $\text{OPT}(\tilde{\theta})$  does not acquire new configurations, i.e.,  $\text{OPT}(\tilde{\theta}) \subseteq \text{OPT}(\theta)$ . If, in addition,  $\text{OPT}(\theta)$  is not consistent, then it will shrink, i.e., the inclusion  $\text{OPT}(\tilde{\theta}) \subset \text{OPT}(\theta)$  is strict.

**Proof.** First, we show that, if  $\Phi_\rho$  stays the same during a single step, then  $\text{OPT}(\theta)$  cannot acquire any new configurations, i.e.,  $\text{OPT}(\tilde{\theta}) \subseteq \text{OPT}(\theta)$ . Again, consider the averaging operation for node  $s$  and consider a tree  $T$  containing this node. Suppose that  $\mathbf{x} \in \text{OPT}(\tilde{\theta}^T)$  and let  $j = x_s$ . Condition  $\Phi_\rho(\tilde{\theta}) = \Phi_\rho(\theta)$  implies that  $\Phi(\tilde{\theta}^T) = \Phi(\theta^T)$  since all values in the sum  $\Phi_\rho(\theta) = \sum_T \rho^T \Phi(\theta^T)$  do not decrease. Therefore, the minimum in (7) is zero, so  $\tilde{\theta}_{s;j}^T = 0$ . This could only have happened if  $\theta_{s;j}^{T'} = 0$  for all trees  $T' \in \mathcal{T}_s$ , which means that  $\mathbf{x}$  was an optimal configuration for vector  $\theta^T$ . We prove that  $\text{OPT}(\tilde{\theta}) \subseteq \text{OPT}(\theta)$ .

Now, suppose that  $\text{OPT}(\theta)$  is not consistent and a complete pass of Step 1 does not change the value of function  $\Phi_\rho$ . It means that, in the beginning of Step 1, the consistency condition for collection  $\text{OPT}(\theta)$  is violated for some element (either a node or an edge). Consider the moment when the algorithm reaches this element. If collection  $\text{OPT}(\theta)$  has already shrunk by that time, then we do not have to prove anything—the lemma holds. Let us assume that  $\text{OPT}(\theta)$  stays the same. Thus, the consistency condition is still violated for this element.

Below, we consider only the case when this element is a node  $s$ , the situation for an edge can be analyzed similarly. Thus, we assume that there exist trees  $T$  and  $T'$  containing the node and configuration  $\mathbf{x}$  with  $x_s = j$  such that  $\mathbf{x}$  is an optimal configuration for vector  $\theta^T$  (so  $\theta_{s;j}^T = 0$ ) but there exists no configuration  $\mathbf{x}'$  with  $x'_s = j$  which is optimal for  $\theta^{T'}$  (so,  $\theta_{s;j}^{T'} > 0$ ). This implies that  $\tilde{\theta}_{s;j}^T > 0$ , therefore, configuration  $\mathbf{x}$  is no longer optimal for  $\tilde{\theta}^T$ . Thus, collection  $OPT(\tilde{\theta})$  has shrunk. The lemma is proven.  $\square$

We now proceed with the proof of Theorem 3.4, Part 2. Let  $\theta^0, \theta^1, \theta^2, \dots$  be the sequence of vectors obtained from one another by applying a complete pass of Step 1 (where  $\theta^0 = \theta$ ). Suppose that function  $\Phi_\rho$  stays the same after any number of steps:  $\Phi_\rho(\theta^0) = \Phi_\rho(\theta^1) = \Phi_\rho(\theta^2) = \dots$ . Let us show that  $\theta$  satisfies the WTA condition.

By Lemma 3.8, we have  $OPT(\theta) \supset OPT(\theta^1) \supset OPT(\theta^2) \supset \dots$ . Since  $OPT(\theta)$  is finite, it cannot shrink indefinitely, therefore, after a finite number of iterations (let us say,  $n$ ),  $OPT(\theta^n)$  will become consistent. We have  $OPT(\theta^n) \subseteq OPT(\theta)$  so, by definition, vector  $\theta$  satisfies the WTA condition. Theorem 3.4 is proven.

### 3.3.2 Proof of Theorem 3.6

To simplify notation, we assume that sequence  $\{\theta^{(i)}\}_i$  is already in the canonical normal form, so  $\tilde{\theta}^{(i)} = \theta^{(i)}$ . Appendix E proves that the sequence  $\{\theta^{(i)}\}_i$  is bounded; therefore, the existence of the converging subsequence follows from the Bolzano-Weierstrass theorem. Part 2) follows from the facts that sequence  $\{\Phi_\rho(\theta^{(i)})\}_i$  is nondecreasing and  $\Phi_\rho$  is continuous. We now prove that, for every converging subsequence  $\{\theta^{(i(m))}\}_{m'}$ , the limit  $\theta^*$  satisfies the WTA condition.

Suppose that this is not true. Let us apply the TRW-S algorithm to vector  $\theta^*$ . Theorem 3.4, Part 2 says that, after a finite number of steps (let us say,  $n$ ), we obtain a configuration  $\tilde{\theta}^*$  such that  $\Phi_\rho(\tilde{\theta}^*) > \Phi_\rho(\theta^*)$ .

Let  $\pi: \mathcal{A} \rightarrow \mathcal{A}$  be a mapping defined as follows: We take vector  $\theta$  and apply  $n$  steps of the TRW-S algorithm. Each step is a continuous mapping  $\mathcal{A} \rightarrow \mathcal{A}$ , therefore,  $\pi$  is continuous as well. Thus,

$$\{\pi(\theta^{(i(m))})\} \xrightarrow{m \rightarrow \infty} \pi(\theta^*) = \tilde{\theta}^*.$$

Function  $\Phi_\rho$  is also continuous, so

$$\{\Phi_\rho(\pi(\theta^{(i(m))}))\} \xrightarrow{m \rightarrow \infty} \Phi_\rho(\tilde{\theta}^*).$$

Thus, there exists index  $m$  such that  $\Phi_\rho(\pi(\theta^{(i(m))})) \geq \Phi_\rho(\theta^*) + \epsilon$ , where  $\epsilon = \frac{1}{2}(\Phi_\rho(\tilde{\theta}^*) - \Phi_\rho(\theta^*)) > 0$ . Note that  $\pi(\theta^{(i(m))}) = \theta^{(n+i(m))}$ . Using Theorem 3.4, Part 2, we get that  $\Phi_\rho(\theta^{(i)}) \geq \Phi_\rho(\theta^*) + \epsilon$  for every index  $i \geq n + i(m)$ , which contradicts Part 2) of the convergence theorem.

## 3.4 TRW-S Algorithm for a Graph with Monotonic Chains

In this section, we focus on Step 1(a)—reparameterizing vector  $\theta^T$ . Recall that its goal is to make sure that the algorithm satisfies the min-marginal property.

For simplicity, consider the case when  $\omega = s$  is a node. In general, a complete inward pass of the ordinary max-product BP is needed for trees  $T \in \mathcal{T}_s$ —sending messages from leaves

to node  $s$  which we treat as a root.<sup>8</sup> However, this would make the algorithm very inefficient if the trees are large. Fortunately, a complete inward pass is not always necessary.

The key idea is that the averaging operation does not invalidate certain messages in trees  $T$  as Proposition 3.9 below shows. In other words, if a message was valid before the operation, then it remains valid after the operation.<sup>9</sup> Therefore, we can “reuse” some of the messages passed in previous steps, i.e., not pass them again.<sup>10</sup>

**Proposition 3.9** *The averaging operation for element  $\omega \in \mathcal{V} \cup \mathcal{E}$  does not invalidate messages in trees  $T \in \mathcal{T}_\omega$  oriented toward  $\omega$ .*

**Proof.** Consider edge  $(s \rightarrow t)$  oriented toward  $\omega$  in tree  $T$ . The averaging operation can affect only the endpoint vector  $\theta_t^T$ . However, condition (2) of a valid message involves vectors  $\theta_s^T$  and  $\theta_{st}^T$ , but not  $\theta_t^T$ .  $\square$

To exploit this property fully, we need to choose trees and the order of averaging operations in a particular way. Specifically, we require trees to be chains which are *monotonic* with respect to some ordering on the graph.

**Definition 3.10.** *Graph  $\mathcal{G}$  and chains  $T \in \mathcal{T}$  are said to be monotonic if there exists an ordering of nodes  $i(u)$ ,  $u \in \mathcal{V}$ , such that each chain  $T$  satisfies the following property: If  $u_1^T, \dots, u_{n(T)}^T$  are the consecutive nodes in the chain, then the sequence  $i(u_1^T), \dots, i(u_{n(T)}^T)$  is monotonic.*

As an example, we could choose  $\mathcal{T}$  to be the set of edges; it is easy to see that they are monotonic for any ordering of nodes. However, it might be advantageous to choose longer trees since the information might propagate faster through the graph.

The algorithm for a graph with monotonic chains is shown in Fig. 2. Its properties are summarized by the following lemma.

**Lemma 3.11.** *Starting with the second pass, the following properties hold during Step 1 for node  $s$ :*

1. *For each edge  $(u, v) \in \mathcal{E}$  with  $i(u) < i(v)$  and  $i(u) < i(s)$ , messages  $(u \rightarrow v)$  in trees  $T \in \mathcal{T}_{uv}$  are valid. This property also holds for node  $u = s$  in the end of Step 1(b).*
2. *For each edge  $(u, v) \in \mathcal{E}$  with  $i(s) < i(u) < i(v)$ , messages  $(v \rightarrow u)$  in trees  $T \in \mathcal{T}_{uv}$  are valid. This property also holds for node  $u = s$  in the beginning and in the end of Step 1(a).*

*In addition, Property 1 holds during the first pass of the algorithm.*

**Proof.** We will use induction. The base of induction is straightforward—right after initialization, the set of messages considered in the lemma is empty.

We need to consider the following cases:

- Assuming that the lemma holds in the beginning of Step 1(a), prove that it holds in the end of Step 1(a).

<sup>8</sup> Note that the outward pass (sending messages from the root to leaves) is not needed. It would convert vectors  $\theta^T$  to normal forms, but would not change vectors  $\theta_s^T$ .

<sup>9</sup> Recall that our algorithm is message-free. As discussed in Section 2.2, the phrase “message is valid for directed edge  $(s \rightarrow t)$  in tree  $T$ ” means that (2) holds (or that sending a message from node  $s$  to node  $t$  would not modify  $\theta_{st;jk}^T$  and  $\theta_{t;k}^T$  except for a constant independent of  $j$  or  $k$ ).

<sup>10</sup> The idea of reusing messages in junction trees was used in the context of iterative proportional fitting [29] and Rao-Blackwellized sampling [21].

0. Initialize  $\theta$  so that  $\theta \in \mathcal{A}$  and  $\sum_T \rho^T \theta^T \equiv \bar{\theta}$ .
1. For nodes  $s \in \mathcal{V}$  do the following operations in the order of increasing  $i(s)$ :
  - (a) Perform the averaging operation for node  $s$ .
  - (b) For every edge  $(s, t) \in \mathcal{E}$  with  $i(t) > i(s)$  do the following:
    - If  $\mathcal{T}_{st}$  contains more than one chain then perform the averaging operation for edge  $(s, t)$  so that vectors  $\theta_s^T$  do not change.
    - For chains in  $\mathcal{T}_{st}$  pass a message from  $s$  to  $t$ .
2. Reverse the ordering: set  $i(u) := |\mathcal{V}| + 1 - i(u)$ .
3. Check whether a stopping criterion is satisfied; if yes, terminate, otherwise go to step 1.

Fig. 2. The TRW-S algorithm for a graph with monotonic chains.

- Assuming that the lemma holds in the beginning of Step 1(b), prove that it holds in the end of Step 1(b).
- Assuming that the lemma holds in the end of Step 1(b) for node  $s$ , prove that it holds in the beginning of Step 1(a) for the next node  $s'$  with  $i(s') = i(s) + 1$ .
- Assuming that the lemma holds in the end of Step 1(b) for the last node, prove that it holds in the beginning of Step 1(a) if the order of nodes is reversed.

The last two cases are straightforward—they do not involve any reparameterization and the set of messages considered in the postcondition is the same as or smaller than the set of messages in the precondition. The first two cases follow from Proposition 3.9 and the fact that, after passing a message from node  $s$  to node  $t$  in tree  $T \in \mathcal{T}_{st}$ , message  $(s \rightarrow t)$  in this tree becomes valid.  $\square$

The lemma implies that starting with the second pass, all messages in trees  $T \in \mathcal{T}_\omega$  oriented toward element  $\omega \in \mathcal{V} \cup \mathcal{E}$  are valid in the beginning of the averaging operation for element  $\omega$ . Therefore, passing messages from leaves to  $\omega$  would not change parameters  $\theta^T$  (except for constants), so the algorithm satisfies the min-marginal property. Note that this property may not hold during the first pass of the algorithm; however, we can treat this pass as a part of initialization. Then, the algorithm in Fig. 2 becomes a special case of the algorithm in Fig. 1.

### 3.4.1 Efficient Implementation

The algorithm in Fig. 2 requires  $O(|\mathcal{T}_s| \cdot |\mathcal{X}_s|)$  storage for node  $s$  and  $O(|\mathcal{T}_{st}| \cdot |\mathcal{X}_s| \cdot |\mathcal{X}_t|)$  storage for edge  $(s, t)$ . However, we can reduce it to  $O(|\mathcal{X}_s|)$  and  $O(|\mathcal{X}_s| + |\mathcal{X}_t|)$ , respectively, using two ideas.<sup>11</sup> First, it can be seen that the algorithm maintains the following equalities:  $\theta_s^T = \theta_s^{T'}$  for  $T, T' \in \mathcal{T}_s$  and  $\theta_{st}^T = \theta_{st}^{T'}$  for  $T, T' \in \mathcal{T}_{st}$  (assuming that they hold after initialization). Second, vectors  $\theta^T$  can be stored using messages  $M_{st} = \{M_{st;k} \mid k \in \mathcal{X}_t\}$  for directed edges  $(s \rightarrow t) \in \mathcal{E}$  according to the following formulas:<sup>12</sup>

$$\theta_t^T = \frac{1}{\rho_t} \left( \bar{\theta}_t + \sum_{(s,t) \in \mathcal{E}} M_{st} \right)$$

$$\theta_{st;jk}^T = \frac{1}{\rho_{st}} (\bar{\theta}_{st;jk} - M_{st;k} - M_{ts;j}).$$

The resulting algorithm is shown in Fig. 3. (We introduced notation  $\gamma_{st} = \rho_{st}/\rho_s$  for directed edge  $(s \rightarrow t) \in \mathcal{E}$ .)

## 4 SUMMARY OF TRW-S ALGORITHM

In the previous section, we described several versions of TRW-S algorithm. For a practical implementation, we recommend using the technique in Fig. 3. We now summarize various algorithmic details.

The input to the algorithm is an energy function specified by parameter vector  $\bar{\theta}$ . The method works by passing messages; for each directed edge  $(s \rightarrow t) \in \mathcal{E}$ , there is message  $M_{st}$  which is a vector with  $|\mathcal{X}_t|$  components. Before running the algorithm, we need to make the following choices:

- Select ordering of nodes  $i(\cdot)$  (i.e., mapping of nodes in  $\mathcal{V}$  onto the set  $\{1, 2, \dots, |\mathcal{V}|\}$ ).
- Select chains  $T \in \mathcal{T}$  which are monotonic with respect to  $i(\cdot)$  (see Definition 3.10). Each edge must be covered by at least one chain.
- Choose probability distribution  $\rho$  over chains  $T \in \mathcal{T}$  such that  $\rho^T > 0$ ,  $\sum_T \rho^T = 1$ .

These choices define coefficients  $\gamma_{st}$  in Fig. 3 in the following way:  $\gamma_{st} = \rho_{st}/\rho_s$ , where  $\rho_{st}$  and  $\rho_s$  are edge and node appearance probabilities, respectively. In other words,  $\gamma_{st}$  is the probability that a tree chosen randomly under  $\rho$  contains edge  $(s, t)$  given that it contains  $s$ .

An important property of our algorithm is that it requires half as much memory compared to traditional BP. Indeed, the latter needs to store messages in both directions for each edge, while we can store only messages oriented *toward* current node  $s$  (or, more precisely, messages that are valid according to Lemma 3.11). The reverse messages are not needed since we update them before they are used. The same space in memory can be used for storing either message  $M_{st}$  or  $M_{ts}$ . The exact moment when  $M_{ts}$  gets replaced with  $M_{st}$  is when edge  $(s, t)$  is processed during Step 1 for node  $s$ .

11. We assume that the storage required for vectors  $\bar{\theta}_{st}$  is negligible. This holds for many energy functions used in practice, e.g., for functions with Potts terms.

12. Note that messages  $M_{st}$  that we use here are slightly different from messages  $M_{st}^{[13]}$  used in [13], [33]. The relationship between the two is as follows:  $M_{st} = \rho_{st} M_{st}^{[13]}$ . We decided to scale the messages because it simplified some of the equations.



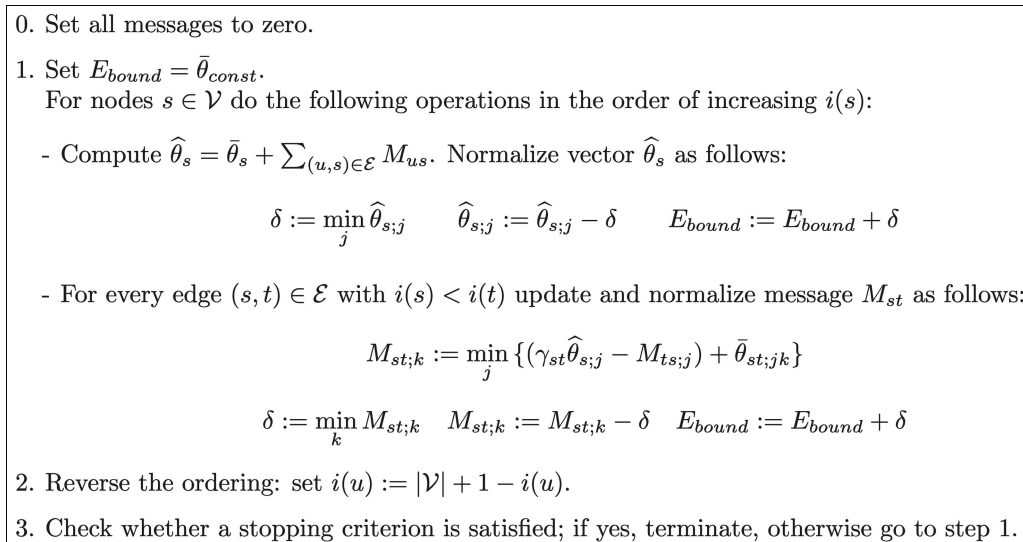


Fig. 3. Efficient implementation of the algorithm in Fig. 2 using messages. For a description of ordering  $i(\cdot)$  and coefficients  $\gamma_{st}$ , see Section 4. In the end of Step 1, value  $E_{bound}$  gives a lower bound on the energy  $E(\mathbf{x} | \bar{\theta})$ . This value cannot decrease with time.

This observation can also be applied to traditional BP with the same schedule of passing messages—we just need to set  $\gamma_{st} = 1$ . The fact that the memory requirements of BP can be reduced by half was first observed in [6]. However, they considered only bipartite graphs and their goal was to simulate the parallel schedule of updating messages. We show that the amount of memory needed can be reduced for any graph. In fact, we give a strict generalization of the technique in [6]. Indeed, the schedule used in [6] is a special case of our sequential schedule if we choose the ordering of nodes such that any node in the first set of a bipartite graphs is before any node in the second set.

Note that, for many important choices of terms  $\bar{\theta}_{st}$ , the message update in Step 1 can be done very efficiently in time  $|\mathcal{X}_t|$  using distance transforms [6]. Then, the complexity of one pass of our algorithm is  $O(|\mathcal{E}| \cdot K)$ , where  $K = \max_s |\mathcal{X}_s|$ .

We conclude this section with the discussion of various implementational details.

#### 4.1 Choice of Node Ordering and Monotonic Chains

Automatic selection of node ordering for an arbitrary graph is an interesting open question which is not addressed in this paper. Intuitively, good ordering should allow long monotonic chains. We tested two types of graphs: 2D grids with four or eight neighborhood system and complete graphs. We used a natural row-major order for the former. Note that, for complete graphs, all orderings are equivalent.

Given an ordering, we constructed monotonic chains in a greedy manner as follows: We select a monotonic chain such that it is not possible to extend it, i.e., for the first node  $s$ , there are no edges  $(u, s)$  with  $i(u) < i(s)$  and, for the last node  $t$ , there are no edges  $(t, v)$  with  $i(v) > i(t)$ . After that, we remove corresponding edges from the graph and repeat the procedure until no edges are left. Thus, we ensure that each edge is covered by exactly one tree. All trees are assigned the uniform probability.

Although this method can produce different sets of trees depending on what chains we choose, the behavior of the TRW-S algorithm is specified uniquely (assuming that the order of nodes is fixed). Indeed, the algorithm depends only

on coefficients  $\gamma_{st} = \rho_{st}/\rho_s$  for edges  $(s \rightarrow t)$ . It can be seen that the number of trees containing node  $s$  is

$$n_s = \max\{|\{(u, s) \in \mathcal{E} : i(u) < i(s)\}|, |\{(s, v) \in \mathcal{E} : i(v) > i(s)\}|\}.$$

Therefore, we have  $\gamma_{st} = 1/n_s$ .

#### 4.2 Stopping Criterion

A conservative way of checking whether the WTA condition has been achieved follows from the definition in Section 3.1: Keep adding minimum configurations to the set  $\mathbf{S}$  until either  $\mathbf{S}$  becomes consistent or no more configurations can be added. This, however, may be expensive. As a practical alternative, we suggest the following heuristic criterion inspired by Theorem 3.4, Part 2: We stop if the value of the lower bound  $E_{bound}$  has not increased (within some precision) during, say, the last 10 iterations. It is worth noting that, even if WTA has been achieved and the lower bound does not change anymore, the messages may still keep changing as well as configuration  $\mathbf{x}$  computed from the messages.

One could also imagine other stopping criteria, e.g., fixing the number of iterations. Different criteria will lead to different tradeoffs between speed and accuracy.

#### 4.3 Choosing Solution

An important question is how to construct solution  $\mathbf{x}$  given reparameterization  $\hat{\theta} = \sum_T \rho^T \theta^T$ . A possible approach is to choose label  $x_s$  for node  $s$  that minimizes  $\hat{\theta}_s(x_s)$ . However, it is often the case that the minimum is not unique within the precision of floating-point numbers. This is not surprising. Indeed, if all nodes have a unique minimum, then it means that we found the optimal solution, as shown in [33]. In general, we cannot expect this since minimizing energy 1 is NP-hard.

Thus, it is essential how we treat nodes with multiple minima. We used the following technique: We assign labels to nodes in some order  $i(s)$  (which, in fact, was the same as in TRW-S algorithm). For node  $s$ , we choose label  $x_s$  that minimizes  $\hat{\theta}_s(x_s) + \sum_{i(u) < i(s)} \hat{\theta}_{us}(x_u, x_s)$ , where the sum is over edges  $(u, s) \in \mathcal{E}$ . In terms of messages, this is equivalent to minimizing  $\hat{\theta}_s(x_s) + \sum_{i(u) < i(s)} \bar{\theta}_{us}(x_u, x_s) + \sum_{i(v) > i(s)} M_{vs}(x_s)$ . This scheme alleviates the problem of multiple minima, but

does not solve it completely. Many nodes may still be assigned essentially at random (more precisely, the solution is determined by numerical errors).<sup>13</sup>

## 5 EXPERIMENTAL RESULTS

We have compared four algorithms: ordinary max-product BP and three tree-reweighted algorithms (TRW-E, TRW-T, TRW-S). The trees and their probabilities have been chosen as described in the previous section.

For the TRW-E and TRW-T algorithms, we also used damping parameter  $\gamma \in (0, 1]$ ; as reported in [33], the algorithms converge if sufficiently damped. For each problem described below, we chose  $\gamma$  as follows: We tried values 0.1, 0.2, ..., 0.9, 1 and determined the average energy after 30 iterations. (The averaging was performed over the different instances of the same problem.) Then, we picked the value with the smallest energy. If the optimal value was  $\gamma = 0.1$ , we kept halving it until the energy started increasing. Note that damping was necessary for TRW-T algorithm, otherwise it always diverged. As for TRW-E algorithm, this was necessary only in some of the cases.

For the ordinary max-product BP algorithm, we implemented the same sequential schedule of updating messages as for TRW-S algorithm. We experimented with the parallel update scheme and found that it was much slower.

### 5.1 Synthetic Problems

We tested the algorithms on two types of graphs: grids  $30 \times 30$  with four-neighborhood system and complete graphs with 50 nodes. Moreover, in each case, we tested the Ising model with attractive potentials and with mixed potentials. Single-node potentials were generated as independent Gaussians:  $\bar{\theta}_{s;0}, \bar{\theta}_{s;1} \sim \mathcal{N}(0, 1)$ . Pairwise potentials were set as follows:  $\bar{\theta}_{st;00} = \bar{\theta}_{st;11} = 0$ ,  $\bar{\theta}_{st;01} = \bar{\theta}_{st;10} = \lambda_{st}$ , where  $\lambda_{st}$  was generated as  $|\mathcal{N}(0, \sigma^2)|$  for attractive potentials and as  $\mathcal{N}(0, \sigma^2)$  for mixed potentials. Parameter  $\sigma$  determines the strength of potentials; we used values  $\sigma \in \{\frac{1}{\sqrt{d}}, \frac{2}{\sqrt{d}}, \frac{3}{\sqrt{d}}\}$ , where  $d$  is the degree of nodes ( $d = 4$  for the grid and  $d = 49$  for the complete graph). We tested the algorithms on 100 sample problems.

As a measure of performance we used two quantities: the value of the lower bound and the energy of current solution (except for the BP algorithm, where we can determine only one of these quantities). Note that the former is a lower bound on the optimal value of the energy and the latter is an upper bound. We plot these quantities as functions of the number of iterations (i.e., the number of passed messages divided by the number of directed edges in the graph). We report only the average values over 100 samples.

Note that, for functions of binary variables, TRW computes that same solution as maxflow algorithm [12]. In particular, for attractive potentials, TRW is guaranteed to find a global minimum, while, for mixed potentials, it finds *part* of an optimal solution. It should also be noted that, in both cases, maxflow would be significantly faster. The goal of this section is to compare different message passing techniques.

13. This technique can be motivated by the following observation: If a reparameterization satisfies WTA condition and the set of nodes with multiple minima consists of disjoint chains which are monotonic with respect to the ordering used, then the procedure will find a global minimum (see [20]).

#### 5.1.1 Attractive Potentials

The results for attractive potentials are shown in Figs. 4a and 4b. Note that, in this case, the global minimum can be found in polynomial time using the maxflow algorithm. In all cases, TRW-S outperforms TRW-E and TRW-T. It also outperforms BP since it converges to the global minimum of the energy, while BP does not. However, in the case of the grid graph, the TRW-S algorithm is slower in the beginning than BP.

#### 5.1.2 Mixed Potentials

The results for this case are shown in Figs. 4c and 4d. The situation is very different from the case of attractive potentials. In all cases, BP outperforms TRW algorithms. We believe that this indicates that LP relaxation (4) is not tight in this case.

## 5.2 Real Problems

### 5.2.1 Binary Segmentation

First, we tested the algorithms on the energy function arising in the method of Boykov and Jolly [2]. This is a function with binary labels where unary data terms come from user-provided hard constraints and learned background and foreground color models and pairwise terms come from image gradients. A regular grid graph with eight-neighborhood system is used. Hard (background) constraints may exist only at the grid boundary; they correspond to a rectangle dragged around the object.

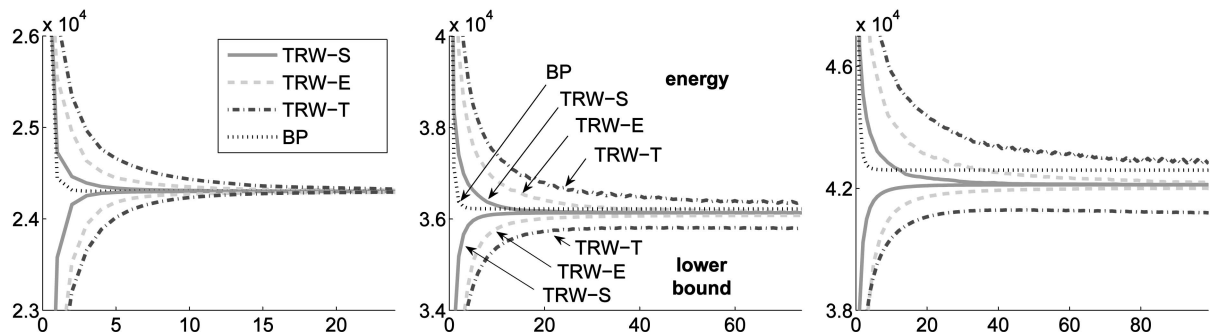
We used 49 different instances with the average size  $1.07 \times 10^5$  nodes. Energy plots are shown in Fig. 5. The average running time for the TRW-S algorithm was 0.067 secs per iteration on a Pentium IV 2.8 GHz processor. For comparison, maxflow algorithm in [1] took 0.114 secs (on average). This shows that, for this problem, maxflow significantly outperforms message passing algorithms.

### 5.2.2 Stereo Matching

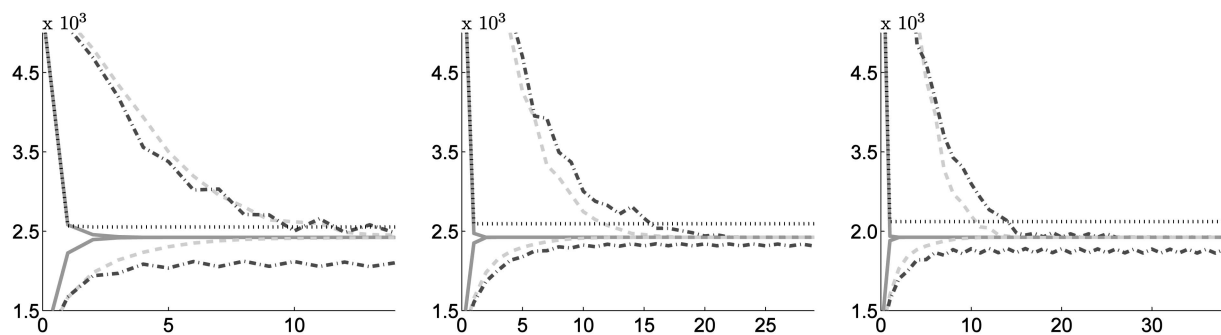
We have tested the algorithms on the energy function arising in the stereo matching problem with Potts interactions [3]. The input is two images taken from different viewpoints and the goal is to find a disparity for every pixel in the left image. We used the four data sets from [23]—Tsukuba, Map, Sawtooth, and Venus. Fig. 5 shows the energy plots and Fig. 6 shows disparity maps for one of the data sets (Tsukuba).

In addition to message passing techniques, we included the results of the expansion move method of Boykov et al. [3], which is referred to as BVZ. (Recall that it is based on the maxflow algorithm.) Note that the horizontal axis for BVZ denotes time; to match it to the number of messages used for other techniques, we used the timing of TRW-S algorithm. Thus, the correspondence between BVZ and other message passing algorithms (TRW-E, TRW-T, BP) is only approximate.<sup>14</sup> Each point in Fig. 5 corresponds to

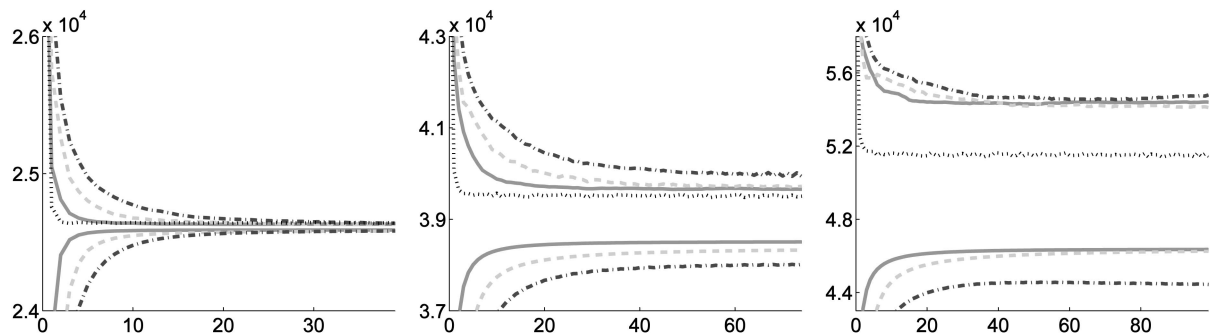
14. In our implementation, one iteration of TRW-E and TRW-T is much slower than TRW-S. One reason is that we have not optimized TRW-E and TRW-T, but there are also objective reasons; for example, TRW-E and TRW-T require at least twice as much memory as TRW-S. On the other hand, in our implementation, one iteration of BP is slightly faster and needs less memory than TRW-S since we use integers for BP and double precision numbers for TRW-S. We also informally tested single precision numbers for TRW-S; then the value of the lower bound becomes very inaccurate, but the value of energy gets worse only slightly.



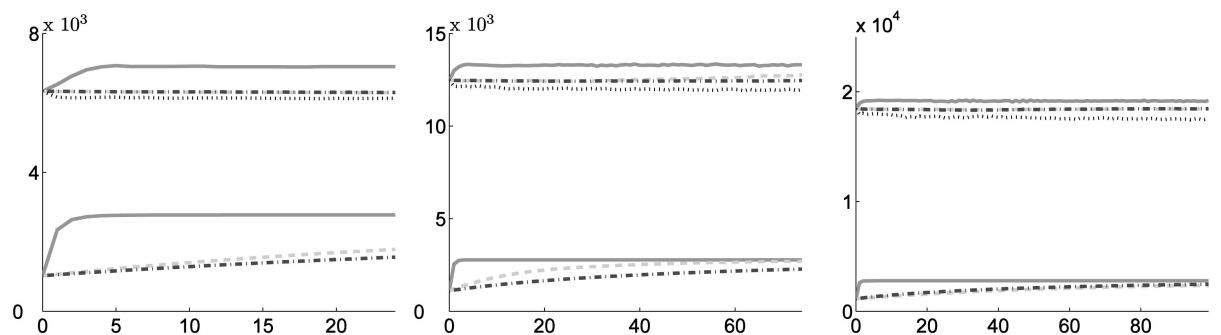
(a)



(b)



(c)



(d)

Fig. 4. Synthetic problems. Horizontal axis: number of iterations. Vertical axis, upper curves: average value of the energy  $E(x | \bar{\theta})$ . Vertical axis, lower curves for TRW algorithms: average value of  $\Phi_\rho(\theta)$ . Columns 1-3: different strengths of the interaction potential ( $\sigma = \frac{1}{\sqrt{d}}, \frac{2}{\sqrt{d}}, \frac{3}{\sqrt{d}}$ ). (a) Grid graph  $30 \times 30$ , attractive potentials. (b) Complete graph with 50 nodes, attractive potentials. (c) Grid graph  $30 \times 30$ , mixed potentials. (d) Complete graph with 50 nodes, mixed potentials.

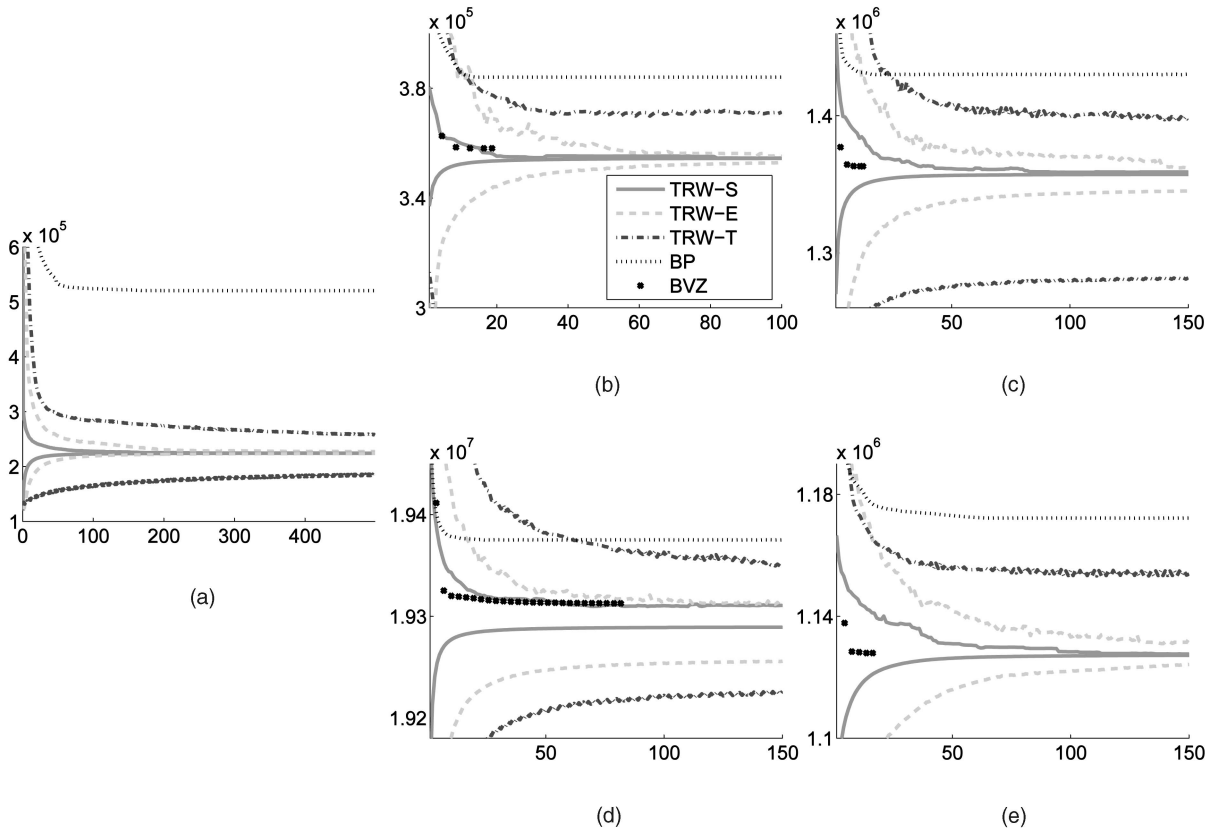


Fig. 5. Results on real problems. For description of BVZ, see text. (a) Binary image segmentation [2] (average over 50 instances), (b), (c), (d), and (e) Stereo (Tsukuba, Map, Sawtooth, and Venus).

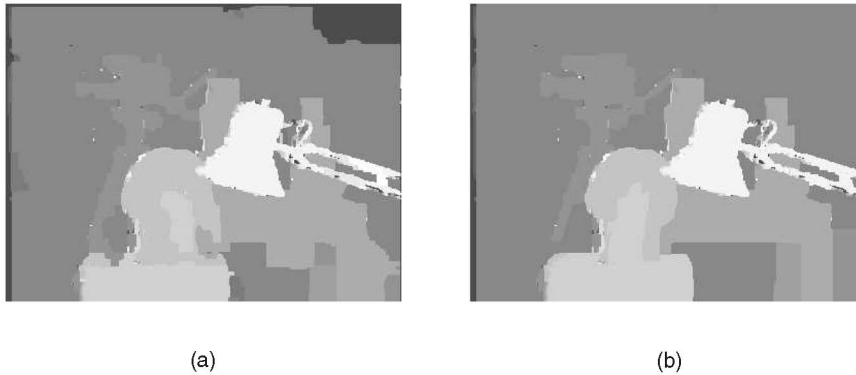


Fig. 6. (a) Result of BP after convergence. (b) Result of TRW-S after 100 iterations. The result of BVZ is visually indistinguishable from the latter.

one iteration of the BVZ algorithm and the last point indicates that BVZ has converged.

TRW-S clearly outperforms other message passing techniques. Compared to BVZ, it is slower in the beginning, but eventually finds lower energy, as shown below:

dataset	size (W x H x D)	TRW-S time	TRW-S accuracy	BVZ accuracy
Tsukuba	384 x 288 x 16	0.348	0.0037%	1.0%
Map	284 x 216 x 30	0.374	0.055%	0.42%
Sawtooth	434 x 380 x 20	0.707	0.096%	0.12%
Venus	434 x 383 x 22	0.822	0.014%	0.061%

Column “TRW-S time” shows the time per one iteration on a Pentium IV 3.2 GHz processor. The column “accuracy” reflects the value of the minimum energy found. For TRW-S,

it is defined as  $\frac{E_{min} - E_{bound}}{E_{bound}} \cdot 100\%$ , where  $E_{min}$  and  $E_{bound}$  are the best values of energy and lower bound, respectively, found during 512 iterations. For BVZ, the accuracy is defined similarly, only  $E_{min}$  is now the value of the energy at convergence.

## 6 DISCUSSION AND CONCLUSIONS

We have developed a new algorithm which can be viewed as a method for direct maximization of objective function  $\Phi_\rho$  subject to the constraint of (6). We gave a precise characterization of local maxima of this function with respect to TRW-S algorithm. We showed that the algorithm is guaranteed to have a subsequence converging to such a maximum.

As with all tree-reweighted algorithms, our method is not guaranteed to find a *global* maximum. Nevertheless, experimental results suggest that this is not an issue for certain synthetic and real problems. For the stereo matching problem, we were able to obtain slightly lower energy than the expansion move algorithm [3], which is considered to be the most accurate energy minimization technique for such problems. On real vision problems that we have tested, TRW-S outperforms both the TRW algorithms in [33] and the ordinary max-product BP.

It should be noted that TRW-S (and TRW algorithms in general) have some limitations. First, they do not work well when LP relaxation (4) is not tight. Second, TRW algorithms are slower than maxflow-based techniques (in cases when such techniques *can* be applied). However, one advantage of message-passing techniques over maxflow-based techniques is that the former are easily parallelizable; one could imagine GPU or hardware implementations. We also believe that TRW-S could be a winner for problems which, on one hand, are sufficiently “easy” in the sense that LP relaxation (4) is tight, but, on the other, do not have a “structured” set of labels so that maxflow-based techniques cannot be applied. It is interesting, for example, to test the problem of super resolution [7].

In our experiments, we noticed that TRW-S algorithm would always converge to a fixed point of TRW, although such convergence would usually take much longer than achieving a weak tree agreement. However, we have not been able to prove this general convergence. On the other hand, achieving convergence may not be necessary since running the algorithm after obtaining WTA will not improve the lower bound on the energy.

## APPENDIX A

### PROPERTIES OF A CANONICAL NORMAL FORM

**Lemma 6.1.** *Suppose that vector  $\theta$  is in a canonical normal form.*

*Then:*

- Constant  $const_{st}$  in (2) is zero:

$$\min_{j \in \mathcal{X}_s} \{\theta_{s;j} + \theta_{st;jk}\} = 0 \quad \forall k \in \mathcal{X}_t. \quad (8)$$

- For a tree-structured graph, (3) for min-marginals can be rewritten as

$$\Phi(\theta) = \theta_{const}, \quad (9a)$$

$$\Phi_{s;j}(\theta) = \theta_{const} + \theta_{s;j}, \quad (9b)$$

$$\Phi_{st;jk}(\theta) = \theta_{const} + \{\theta_{s;j} + \theta_{st;jk} + \theta_{t;k}\}. \quad (9c)$$

**Proof.** The fact that constant  $const_{st}$  in (2) is zero can be derived as follows: Let us add  $\theta_{t;k}$  to this equation:

$$\min_{j \in \mathcal{X}_s} \{\theta_{s;j} + \theta_{st;jk} + \theta_{t;k}\} = \theta_{t;k} + const_{st} \quad \forall k \in \mathcal{X}_t.$$

Now, take the minimum over  $k \in \mathcal{X}_t$ . By the definition of a canonical normal form, we get zero on the LHS and  $const_{st}$  on the RHS, i.e.,  $0 = const_{st}$ . The first property is proven.

Now, assume that the graph is a tree. Let  $\mathbf{x}^*$  be an optimal configuration for vector  $\theta$  (then,  $E(\mathbf{x}^* | \theta) = \Phi(\theta)$ ). For a fixed node  $s \in \mathcal{V}$ , the minimum of  $\theta_s(j)$  among  $j \in \mathcal{X}_s$  is achieved at  $j = x_s^*$  (due to (3a)). By the definition of a canonical normal form, the value of this minimum is zero. Thus,  $\theta_s(x_s^*) = 0$ . Using the same reasoning for edge  $(s, t) \in \mathcal{E}$ , we get that  $\theta_s(x_s^*) + \theta_{st}(x_s^*, x_t^*) + \theta_t(x_t^*) = 0$ , which implies that  $\theta_{st}(x_s^*, x_t^*) = 0$ . Therefore,

$$\Phi(\theta) = \theta_{const} + \sum_{s \in \mathcal{V}} \theta_s(x_s^*) + \sum_{(s,t) \in \mathcal{E}} \theta_{st}(x_s^*, x_t^*) = \theta_{const}.$$

Now, for node  $s \in \mathcal{V}$ , let us plug  $j = x_s^*$  into (3a). The LHS is  $\Phi(\theta)$  and the RHS is  $const_s$ . Therefore,  $const_s = \Phi(\theta) = \theta_{const}$ . Similarly, we can derive that  $const_{st} = \Phi(\theta) = \theta_{const}$  in (3b). The second property is proven.  $\square$

## APPENDIX B

### REPARAMETERIZATION AND MESSAGES

As discussed in Section 2.2, any message vector defines a reparameterization. We now show that the converse is also true: Any reparameterization can be described via messages, up to a *constant parameter vector*.

**Definition 6.2.** *Vector  $\tilde{\theta} \in \mathbb{R}^d$  is called a constant parameter vector if, for each node  $s \in \mathcal{V}$ ,  $j \in \mathcal{X}_s$ , and for each edge  $(s, t) \in \mathcal{E}$ ,  $(j, k) \in \mathcal{X}_s \times \mathcal{X}_t$ , values  $\tilde{\theta}_{s;j}$  and  $\tilde{\theta}_{st;jk}$  are constants independent of  $j, k$ .*

**Lemma 6.3.** *Suppose that  $\theta^2 \equiv \theta^1$  (i.e.,  $\theta^2$  is a reparameterization of  $\theta^1$ ). Then, there exists message vector  $M$  and constant parameter vector  $\tilde{\theta}$  such that  $\theta^2 = \theta^1[M] + \tilde{\theta}$  and  $\tilde{\theta} \equiv 0$ .*

**Proof.** The following properties will be quite useful in the proof:

(P1) For any vectors  $\theta$ ,  $\theta'$ , and  $M$ , there holds  $(\theta + \theta')[M] = \theta[M] + \theta' = \theta + \theta'[M]$ .

(P2) For any vectors  $\theta$ ,  $M$ , and  $M'$ , there holds  $\theta[M + M'] = \theta[M][M']$ .

In addition, we will need the following proposition.

**Proposition 6.4.** *For any edge  $(s, t) \in \mathcal{E}$  and variables  $j, j' \in \mathcal{X}_s$ ,  $k, k' \in \mathcal{X}_t$*

$$\theta_{st;jk}^1 + \theta_{st;j'k'}^1 - \theta_{st;jk'}^1 - \theta_{st;j'k}^1 = \theta_{st;jk}^2 + \theta_{st;j'k'}^2 - \theta_{st;jk'}^2 - \theta_{st;j'k}^2.$$

**Proof.** Let  $\mathbf{x}^{jk}, \mathbf{x}^{j'k}, \mathbf{x}^{jk'}, \mathbf{x}^{j'k'} \in \mathcal{X}$  be four configurations such that they agree on all nodes other than  $s$  and  $t$  and

$$x_s^{jk} = j, x_t^{jk} = k \quad x_s^{j'k} = j, x_t^{j'k} = k',$$

$$x_s^{jk'} = j', x_t^{jk'} = k \quad x_s^{j'k'} = j', x_t^{j'k'} = k'.$$

We can write

$$\begin{aligned} E(\mathbf{x}^{jk} | \theta^1) + E(\mathbf{x}^{j'k'} | \theta^1) - E(\mathbf{x}^{jk'} | \theta^1) - E(\mathbf{x}^{j'k} | \theta^1) \\ = \theta_{st;jk}^1 + \theta_{st;j'k'}^1 - \theta_{st;jk'}^1 - \theta_{st;j'k}^1 \end{aligned}$$

—it is easy to see that all other terms cancel each other. We can write a similar expression for vector  $\theta^2$ . Since  $\theta^1 \equiv \theta^2$ , the expressions on the LHS are equal. Therefore, the expressions on the RHS are equal as well, which gives us the desired result.  $\square$

We now proceed with the proof of the lemma. Let  $\theta = \theta^1 - \theta^2$ . As shown in [32], there exists a message vector  $M$  such that  $\tilde{\theta} = \theta[M]$  is a fixed point of max-product BP. We have

$$\theta^1[M] = \theta^2 + (\theta^1 - \theta^2)[M] = \theta^2 + \theta[M] = \theta^2 - (-\tilde{\theta}).$$

Also,  $\theta^1 \equiv \theta^2$  implies that  $\tilde{\theta} \equiv \theta \equiv \mathbf{0}$ . Thus, we can prove Lemma 6.3 by proving that  $\theta$  is a constant parameter vector.

We can convert  $\tilde{\theta}$  to a canonical normal form  $\hat{\theta}$  by adding a constant parameter vector. We will prove that  $\theta = \mathbf{0}$ .

Consider an edge  $(s, t) \in \mathcal{E}$ . Since  $\hat{\theta}$  is a reparameterization of a constant function, by Proposition 6.4, we have

$$\hat{\theta}_{st;jk} + \hat{\theta}_{st;jk'} - \hat{\theta}_{st;jk} - \hat{\theta}_{st;jk'} = 0 \quad (10)$$

for all variables  $j, j' \in \mathcal{X}_s, k, k' \in \mathcal{X}_t$ . Condition (8) for a canonical normal form yields the following formulas:

$$\min_{j \in \mathcal{X}_s} \{\hat{\theta}_{s;j} + \hat{\theta}_{st;jk}\} = 0 \quad \forall k \in \mathcal{X}_t, \quad (11a)$$

$$\min_{k \in \mathcal{X}_t} \{\hat{\theta}_{t;k} + \hat{\theta}_{st;jk}\} = 0 \quad \forall j \in \mathcal{X}_s. \quad (11b)$$

Let us prove that  $\hat{\theta}_{st;jk} \leq 0$  for every  $(j, k) \in \mathcal{X}_s \times \mathcal{X}_t$ . Let  $j'$  and  $k'$  be the variables that minimize (11a) and (11b), respectively; then  $\hat{\theta}_{s;j'} + \hat{\theta}_{st;j'k} = \hat{\theta}_{t;k'} + \hat{\theta}_{st;j'k} = 0$ . Using (10), we get

$$\hat{\theta}_{st;jk} = \hat{\theta}_{st;j'k} + \hat{\theta}_{st;jk'} - \hat{\theta}_{st;j'k'} = -\hat{\theta}_{s;j'} - \hat{\theta}_{t;k'} - \hat{\theta}_{st;j'k'}.$$

The expression on the RHS is nonpositive by the definition of a canonical normal form.

Now, let us prove that  $\hat{\theta}_{st;jk} = 0$  for every  $(j, k) \in \mathcal{X}_s \times \mathcal{X}_t$ . Let  $j^*$  and  $k^*$  be the variables that minimize  $\hat{\theta}_{s;j'}$  over  $j'$  and  $\hat{\theta}_{t;k'}$  over  $k'$ , respectively; then  $\hat{\theta}_{s;j^*} = \hat{\theta}_{t;k^*} = 0$ . Using (11a) for  $k$  and  $k^*$  and (11b) for  $j$ , we conclude that  $\hat{\theta}_{st;j^*k} \geq 0$ ,  $\hat{\theta}_{st;j^*k^*} \geq 0$  and  $\hat{\theta}_{st;jk^*} \geq 0$ . Therefore,  $\hat{\theta}_{st;j^*k} = \hat{\theta}_{st;j^*k^*} = \hat{\theta}_{st;jk^*} = 0$ . Finally,

$$\hat{\theta}_{st;jk} = \hat{\theta}_{st;j^*k} + \hat{\theta}_{st;jk^*} - \hat{\theta}_{st;j^*k^*} = 0.$$

The fact that  $\hat{\theta}_{st} = \mathbf{0}$  for all edges tells us that nodes are independent. We also know that  $E(\mathbf{x} | \hat{\theta})$  is zero for any configuration  $\mathbf{x}$ . By considering configurations which agree on all nodes except node  $s$ , we conclude that  $\hat{\theta}_{s;j} = \text{const}_s$  for any  $j \in \mathcal{X}_s$ . This constant must be zero since  $\hat{\theta}$  is in a canonical form.

We have shown that  $\hat{\theta}_s = \mathbf{0}$  for all nodes  $s$  and that  $\hat{\theta}_{st} = \mathbf{0}$  for all edges  $(s, t)$ , i.e., that  $\hat{\theta}_s$  is a constant parameter vector. Lemma 6.3 is proven.  $\square$

## APPENDIX C

### PROOF OF LEMMA 3.1

Let us prove the following lemma first.

**Lemma 6.5.** *If  $\theta^1 \equiv \theta^2$ , then, for any vector  $\tau \in \text{LOCAL}(\mathcal{G})$ , there holds  $\langle \theta^1, \tau \rangle = \langle \theta^2, \tau \rangle$ .*

**Proof.** By Lemma 6.3 in Appendix B, there exists message vector  $M$  and constant parameter vector  $\tilde{\theta}$  such that  $\theta^2 = \theta^1[M] + \tilde{\theta}$ . We will show that  $\langle \theta^1[M], \tau \rangle = \langle \theta^1, \tau \rangle$  and  $\langle \tilde{\theta}, \tau \rangle = 0$  for any  $\tau \in \text{LOCAL}(\mathcal{G})$ .

Case 1. Since  $\theta^1[M] = \theta^1 + \mathbf{0}[M]$ , it suffices to show that  $\langle \mathbf{0}[M], \tau \rangle = 0$ . Moreover, due to Property  $\mathcal{P}2$  in Appendix B, it is enough to prove this for vectors  $M$  with a single nonzero element. Let  $M_{st;k}$  be this element. Then, the only nonzero elements of  $\theta = \mathbf{0}[M]$  are  $\theta_{t;k} = M_{st;k}$  and  $\theta_{st;jk} = -M_{st;k}$  for all  $j \in \mathcal{X}_s$ . We can write

$$\begin{aligned} \langle \mathbf{0}[M], \tau \rangle &= \theta_{t;k} \cdot \tau_{t;k} + \sum_j \theta_{st;jk} \cdot \tau_{st;jk} \\ &= (\tau_{t;k} - \sum_j \tau_{st;jk}) \cdot M_{st;k} = 0 \end{aligned}$$

since  $\tau \in \text{LOCAL}(\mathcal{G})$ .

Case 2.  $\tilde{\theta}$  is a constant parameter vector, so  $\tilde{\theta}_{s;j} = c_s$  and  $\tilde{\theta}_{st;jk} = c_{st}$ , where  $c_s$  and  $c_{st}$  are constants independent of  $j, k$ . We can write

$$\begin{aligned} \langle \tilde{\theta}, \tau \rangle &= \tilde{\theta}_{const} + \sum_{s \in \mathcal{V}} \sum_j \tilde{\theta}_{s;j} \cdot \tau_{s;j} + \sum_{(s,t) \in \mathcal{E}} \sum_{j,k} \tilde{\theta}_{st;jk} \cdot \tau_{st;jk} \\ &= \tilde{\theta}_{const} + \sum_{s \in \mathcal{V}} c_s \left( \sum_j \tau_{s;j} \right) + \sum_{(s,t) \in \mathcal{E}} c_{st} \left( \sum_{j,k} \tau_{st;jk} \right) \\ &= \tilde{\theta}_{const} + \sum_{s \in \mathcal{V}} c_s + \sum_{(s,t) \in \mathcal{E}} c_{st}, \end{aligned}$$

so it is a constant independent of  $\tau$ . Plugging  $\tau = \phi(\mathbf{x})$  for some configuration  $\mathbf{x} \in \mathcal{X}$ , we conclude that this constant is zero.  $\square$

Now, we can prove Lemma 3.1. Let  $\theta^*$  be a vector maximizing problem (5). Clearly, it satisfies constraints of (6). Now, consider another vector  $\theta \in \mathcal{A}$  such that  $\hat{\theta} = \sum_T \rho^T \theta^T$  is a reparameterization of  $\tilde{\theta}$ . We can write

$$\begin{aligned} \Phi_\rho(\theta) &\leq \max_{\theta \in \mathcal{A}, \sum_T \rho^T \theta^T = \hat{\theta}} \Phi_\rho(\theta) \\ &= \min_{\tau \in \text{LOCAL}(\mathcal{G})} \langle \hat{\theta}, \tau \rangle = \min_{\tau \in \text{LOCAL}(\mathcal{G})} \langle \tilde{\theta}, \tau \rangle = \Phi_\rho(\theta^*), \end{aligned}$$

where the first and the third equality follow from Theorem 2.1 and the second equality follows from Lemma 3.1. Therefore,  $\theta^*$  maximizes (6).

## APPENDIX D

### LOCAL MAXIMA OF TRW-S ALGORITHM

As we proved, any vector  $\theta$  that maximizes (6) must satisfy the WTA condition. Here, we show the converse is not necessarily true. We give an example of vectors  $\theta$  and  $\tilde{\theta}$  such that they both satisfy the WTA condition and  $\sum_T \rho^T \tilde{\theta}^T \equiv \sum_T \rho^T \theta^T$ , but  $\Phi_\rho(\tilde{\theta}) \neq \Phi_\rho(\theta)$ .

The graph with two trees is shown in Fig. 7. Vectors  $\theta = \{\theta^1, \theta^2\}$  and  $\tilde{\theta} = \{\tilde{\theta}^1, \tilde{\theta}^2\}$  are given as follows: All single-node potentials are zero:  $\theta_{s;j}^T = \tilde{\theta}_{s;j}^T = 0$ . The constant terms are  $\theta_{const}^T = 0$ ,  $\tilde{\theta}_{const}^T = 0.5$ . Other elements of vectors  $\theta^1$  and  $\theta^2$  are given by

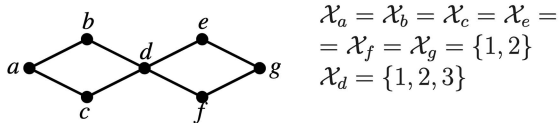


Fig. 7. Graph for the example in Appendix D. Nodes  $a, b, c, e, f, g$  have two states and node  $d$  has three states. There are two trees with equal probabilities:  $T_1 = (a, b, d, e, g)$  and  $T_2 = (a, c, d, f, g)$ .

$$\begin{aligned} \theta_{ab}^1 &= \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} & \theta_{bd}^1 &= \begin{bmatrix} 0 & 2 & 2 \\ 2 & 0 & 0 \end{bmatrix} & \theta_{de}^1 &= \begin{bmatrix} 2 & 0 \\ 0 & 2 \\ 2 & 0 \end{bmatrix} \\ \theta_{eg}^1 &= \begin{bmatrix} 0 & 2 \\ 2 & 0 \end{bmatrix} & \theta_{ac}^2 &= \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} & \theta_{cd}^2 &= \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 2 \end{bmatrix} \\ \theta_{df}^2 &= \begin{bmatrix} 2 & 0 \\ 2 & 0 \\ 0 & 2 \end{bmatrix} & \theta_{fg}^2 &= \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \end{aligned}$$

and elements of vectors  $\tilde{\theta}^1$  and  $\tilde{\theta}^2$ —by

$$\begin{aligned} \tilde{\theta}_{ab}^1 &= \begin{bmatrix} 3 & 0 \\ 0 & 1 \end{bmatrix} & \tilde{\theta}_{bd}^1 &= \begin{bmatrix} 0 & 1 & 1 \\ 3 & 0 & 0 \end{bmatrix} & \tilde{\theta}_{de}^1 &= \begin{bmatrix} 0 & 0 \\ 0 & 4 \\ 0 & 0 \end{bmatrix} \\ \tilde{\theta}_{eg}^1 &= \begin{bmatrix} 0 & 4 \\ 0 & 0 \end{bmatrix} & \tilde{\theta}_{ac}^2 &= \begin{bmatrix} 1 & 0 \\ 0 & 3 \end{bmatrix} & \tilde{\theta}_{cd}^2 &= \begin{bmatrix} 3 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix} \\ \tilde{\theta}_{df}^2 &= \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 4 \end{bmatrix} & \tilde{\theta}_{fg}^2 &= \begin{bmatrix} 4 & 0 \\ 0 & 0 \end{bmatrix}. \end{aligned}$$

Condition  $\sum_T \rho^T \tilde{\theta}^T \equiv \sum_T \rho^T \theta^T$  can be checked using the definition of reparameterization. It is easy to see that all tree vectors are in a canonical normal form and WTA condition is satisfied for both  $\theta$  and  $\tilde{\theta}$ . However, we have  $\Phi_\rho(\theta) = 0$  and  $\Phi_\rho(\tilde{\theta}) = 0.5$ .

This example applies not only to TRW-S, but also to TRW-E and TRW-T algorithms. Indeed, it is not difficult to see that vector  $\theta$  is a fixed point of TRW algorithms.

Note that, in the example above, one of the nodes has three possible states. This is not accidental: If all nodes have binary states, then the WTA condition always yields a global maximum of the lower bound, as our paper, Kolmogorov and Wainwright, shows [12].

## APPENDIX E

### PROOF OF THEOREM 3.6

We now show that vectors  $\theta \in \{\theta^{(i)}\}_i$  are bounded (assuming that they are in the canonical normal form). We will do it in three steps: First, we show that elements  $\theta_{const}^T$  are bounded, then we show that, for each node  $s \in \mathcal{V}^T$ , vectors  $\theta_s^T$  are bounded, and, finally, we show that, for each edge  $(s, t) \in \mathcal{E}^T$ , vectors  $\theta_{st}^T$  are bounded.

Case 1. According to Theorem 3.4, Part 1, terms  $\Phi(\theta^T)$  are nondecreasing. By Lemma 6.1, we have  $\theta_{const}^T = \Phi(\theta^T)$ . This shows that  $\theta_{const}^T$  are bounded from below. The following inequality then implies that they are also bounded from above:

$$\sum_T \rho^T \theta_{const}^T = \sum_T \rho^T \Phi(\theta^T) \leq \Phi(\bar{\theta}).$$

Case 2. Consider node  $s \in \mathcal{V}$  and variable  $j \in \mathcal{X}_s$ . By definition of the canonical normal form, elements  $\theta_{s;j}^T$  are bounded from below. To prove that they are bounded from above, we derive an inequality similar to the previous one.

We use function  $\Phi_{s;j}$  for this purpose. It is a minimum of a finite number of linear functions and, thus, is concave. Applying Jensen's inequality yields

$$\begin{aligned} \sum_T \rho^T (\theta_{const}^T + \theta_{s;j}^T) \\ = \sum_T \rho^T \Phi_{s;j}(\theta^T) \leq \Phi_{s;j} \left( \sum_T \rho^T \theta^T \right) = \Phi_{s;j}(\bar{\theta}). \end{aligned}$$

We already showed that  $\theta_{const}^T$  are bounded, so this implies that  $\theta_{s;j}^T$  are bounded from above.

Case 3. Consider an edge  $(s, t) \in \mathcal{V}$  and variables  $(j, k) \in \mathcal{X}_s \times \mathcal{X}_t$ . By definition of the canonical normal form,  $\theta_{s;j}^T + \theta_{st;jk}^T + \theta_{t;k}^T \geq 0$ . It implies that  $\theta_{st;jk}^T$  is bounded from below since  $\theta_{s;j}^T$  and  $\theta_{t;k}^T$  are bounded. The proof that it is bounded from above is completely analogous to the previous case; we just need to use function  $\Phi_{st;jk}$ .

## ACKNOWLEDGMENTS

The author would like to thank Thomas Minka for helpful discussions, the anonymous reviewers for suggestions that helped to improve the presentation of the paper, and Philip Torr for careful proofreading of the manuscript. This work was mainly done while the author was with Microsoft Research, Cambridge.

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