Supplementary Materials for: Improved Tampering Localization in Digital Image Forensics based on Maximal Entropy Random Walk

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I. Incorporation of the Markovian Prior

We resort to the popular Ising model to incorporate the Markovian prior in the final decision. Tampering localization is expressed as a labelling problem, where the binary label $t_i \in \{0, 1\}$ will denote either authentic ($t_i = 0$) or tampered ($t_i = 1$) decisions. The decision for every block t_i depends on up to 4 of its closest neighbors, i.e., blocks $t_j : j \in \Xi_i = \{i-1, i+1, i-N_h, i+N_h\}$ where N_h denotes image height (in blocks). Obviously, at the image borders the set of neighbors Ξ_i needs to be pruned accordingly.

We minimize the following energy function:

$$\sum_{i=1}^{N} E_\tau(c_i^{(s)}, t_i) + \alpha \sum_{i=1}^{N} t_i + \beta \sum_{i=1}^{N} \sum_{j \in \Xi_i} |t_i - t_j| \ . \tag{1}$$

where α represents the penalty for every tampered block (decision bias), and β the penalty for different decisions among neighbors (interaction strength). Since the values from the response maps correspond to the probability that a given image block is tampered, the data terms could be obtained as $-\log(c_i)$ and $-\log(1 - c_i)$, respectively. However, we use the following generalization [1]:

$$E_\tau(c, t) = -\log\, \max(\Psi_{\text{min}}, \Psi_\tau(c, t)), \tag{2}$$

with $\Psi_{\text{min}} \in [0, 1]$ and:

$$\Psi_\tau(c, t) = \begin{cases} 1 - \frac{c}{2\tau} & \text{for } t = 0, \\ 1 + \frac{c}{2(1-\tau)} - \frac{1}{2(1-\tau)} & \text{for } t = 1, \end{cases} \tag{3}$$

where $\tau \in (0, 1)$ is a quasi-threshold that equalizes potentials for both decisions[1], i.e., $E_\tau(\tau, 0) = E_\tau(\tau, 1)$. The shape of the adopted energy function, and the impact of the quasi-threshold is shown in Fig. 1. Setting a minimal value Ψ_{min} prevents the nodes from becoming fixed to certain decisions (due to infinite energy). We set $\Psi_{\text{min}} = 0.001$ based on preliminary experiments.

To minimize the above energy function, we used a graph cuts-based solver [3, 4] from the UGM toolbox [5]. For this localization method, we refrain from ad-hoc map cleaning, and allow the Markovian prior to deal with false-positives. However, to facilitate stronger neighborhood interactions, we compensate for excessive erosion of the detection boundary by peforming morphological dilation. The parameters (α, β) were chosen with grid search.

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[1]The decision bias α has similar impact, and can also be used for controlling the classification trade-offs under fixed τ; such an approach was used, e.g., in [2]. However, in our experiments it gave worse results.

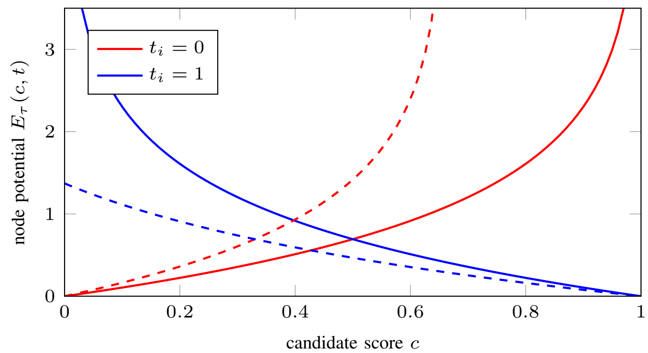

Fig. 1. Energy of the data term for both decision labels $t_i = 0$ and $t_i = 1$; $\tau = 0.5$ (solid); $\tau = 0.33$ (dashed).

Fig. 2. Forty representative response maps used for parameter optimization.

II. Parameter Optimization

We used grid search to find the optimal parameters for both the energy-minimization approach (α, β), and the proposed MERW-based method (σ_1^2, σ_2^2). The objective was to maximize the area under the ROC curve $t_p(f_p)$ for a representative sub-set of 40 images (10 per tampering pattern, Fig. 2):

$$(\hat{\alpha}, \hat{\beta}) = \underset{(\alpha,\beta)}{\text{argmax}}\ \frac{1}{0.2} \int_0^{0.2} \tilde{t_p}(f_p|\alpha, \beta) df_p \tag{4}$$

For the proposed approach, the problem is analogous with maximization over (σ_1^2, σ_2^2). Restriction to the range $f_p \in [0, 0.2]$ stems from marginal usability of configurations with higher false positive rates, and from difficulties in finding a universal set of parameters for the energy minimization approach that would be beneficial for the whole ROC curve. We obtained the ROC characteristic by changing the threshold τ, non-uniformly distributed in $[0, 1]$ to yield more samples for low f_p rates. Values between sampled points were filled with spline interpolation to obtain a smooth curve $\tilde{t_p}(f_p)$.

The behavior of the optimization objective is shown in Fig. 3. The best configuration is depicted with a white marker. The color maps span the range [0.82,0.8625] for MERW and [0.82,0.845] for the energy minimization approach.

III. Practical Implementation Notes

All stages of the described algorithm, starting from computation of the weight matrix to finding the stationary probability

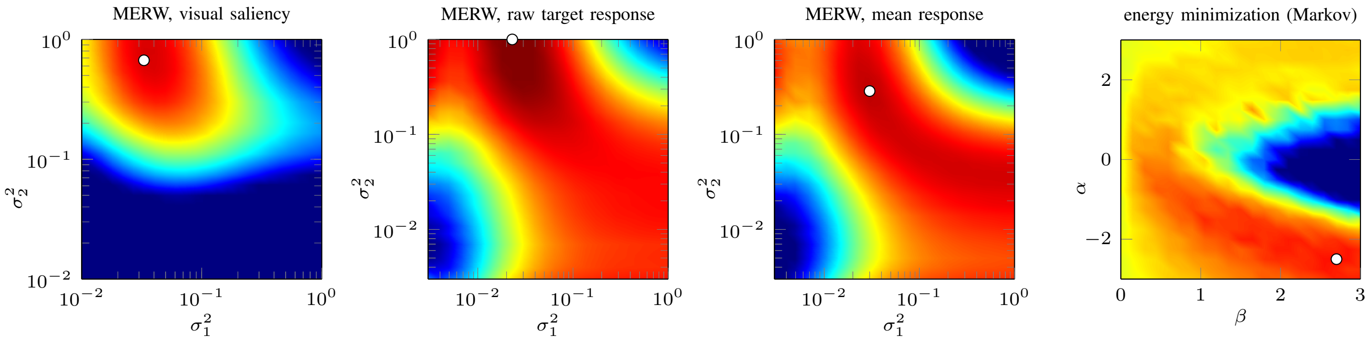

Fig. 3. Behavior of the optimization objective (area under ROC curve for low false positive error rates) during grid search for the optimal parameters of the considered localization methods; the best configuration is depicted with a white marker; the color maps span the range [0.82,0.8625] for MERW and [0.82,0.845] for the energy minimization approach and change from blue to red towards greater values;

density, can be easily implemented in parallel. In order to quickly find the eigenvector corresponding to the greatest eigenvalue, we use the power iteration method. Starting in iteration $k = 0$ with a vector of ones $\mathbf{u}^{(0)} := 1$, we compute successive approximations:

$$\mathbf{u}^{(k+1)} = \frac{\mathbf{W}\mathbf{u}^{(k)}}{||\mathbf{W}\mathbf{u}^{(k)}||} \tag{5}$$

until the relative improvement falls below a certain threshold (set to 10^{-6} for evaluation, and 10^{-4} for parameter search) or the number of iterations exceeds 100. The $||\cdot||$ operator denotes the L2 norm. If necessary (for asymmetrical weights) we repeat the procedure to find $\mathbf{v}$ - the eigenvector of $\mathbf{W}^T$.

We implemented the proposed scheme in C++. When executed with 8 parallel threads, the complete algorithm (2 consecutive instances of MERW; inclusive of input / output operations) typically takes 1-3 seconds (depending on the number of iterations) on a Core i7-4790 CPU processor (3.60GHz). The input tampering maps were of size 64×64 (corresponding to a 512×512 px image).

Our current implementation uses a fully connected graph spanned on 8×8 px blocks and stored in the memory as a dense matrix. Such an approach has potential scalability issues since the graph matrix size changes as $O(n^2)$ which leads to quadratic complexity both in terms of computational resources and memory. Tampering localization within 2 Mpx images (1920×1080 px) is still effortless for modern desktop PCs - requires ≈4 GB of RAM and takes around 20-30 seconds to compute both MERWs. However, dealing with full-resolution photographs is no longer feasible with the current implementation. Several techniques could be used to address this limitation, like using larger image blocks / segments, adopting sparse matrix representation, or considering approximations of MERW [6]. However, the issue is out of scope of this study.

References

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