

Forgery  
authentication using  
distortion cue and  
fake saliency map  
essay



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The widespread availability of photo manipulation software has made it unprecedentedly easy to manipulate images for malicious purposes. Image splicing is one such form of tampering.

In recent years, researchers have proposed various methods for detecting such splicing. In this paper, we present a novel method of detecting splicing in images, using discrepancies in motion blur. We use motion blur estimation through image gradients in order to detect inconsistencies between the spliced region and the rest of the image. We also develop a new measure to assist in inconsistent region segmentation in images that contain small amounts of motion blur. Experimental results show that our technique provides good segmentation of regions with inconsistent motion blur. We also provide quantitative comparisons with other existing blur-based techniques over a database of images.

It is seen that our technique gives significantly better detection results. Distortion is often considered as an unfavorable factor in most image analysis. However, it is undeniable that the distortion reflects the intrinsic property of the lens, especially, the extreme wide-angle lens, which has a significant distortion. In this paper, we discuss how explicitly employing the distortion cues can detect the forgery object in distortion image and make the following contributions: 1) a radial distortion projection model is adopted to simplify the traditional captured ray-based models, where the straight world line is projected into a great circle on the viewing sphere; 2) two bottom-up cues based on distortion constraint are provided to discriminate the authentication of the line in the image; 3) a fake saliency map is used to maximum fake detection density, and based on the fake saliency map, an <https://assignbuster.com/forgery-authentication-using-distortion-cue-and-fake-saliency-map-essay/>

energy function is provided to achieve the pixel-level forgery object via graph cut. Experimental results on simulated data and real images demonstrate the performances of our method. Existing System The power of the visual medium is compelling and so, malicious tampering can have significant impact on people's perception of events.

Misleading images are used for introducing psychological bias, sensationalizing news, political propaganda, and propagating urban myths. The image in Fig. 1, taken from [1], is an instance of the latter. This photograph was widely circulated via e-mail, supposedly having been obtained from a camera found in the debris of the World Trade Center buildings after the attacks of September 11, 2001. The approaching aircraft in the background seems to imply that this image was captured mere seconds before the impact.

However, this image is clearly fake. Many techniques have been developed to discover splicing and compositing of images. Statistical analyses and lighting inconsistencies may be used in order to detect image tampering. Other methods involve exploiting certain features of images which are characteristic of the imaging systems, formats, and the environment. Proposed System This paper is an extension of our work reported in [1]. We change the motion blur estimation technique from spectral matting to image gradients for faster processing.

We refine the segmentation process in order to provide better results and deal with cases of more complex blurs. We develop new measures in order to reduce the amount of human intervention needed in our technique and

improve its robustness. We also provide a detailed quantitative analysis of the efficiency of our technique and test our technique on a database of images. we present a novel Binary Partitioning Tree analysis work for Semi-supervised image segmentation, which shows the suitability for the application of forged object extraction. From an over-segmentation result and the generated BPT, the proposed BPT analysis algorithm automatically selects an appropriate subset of nodes to represent a more meaningful segmentation result.

One is that a novel dissimilarity measure considering the impact of color difference, area factor and adjacency degree in a unified way is proposed for region merging and used in the BPT generation process. The other is the proposed BPT analysis algorithm, in which the node evaluation is designed to reasonably identify forged regions, and the following two- phase node selecting process guarantees a meaningful segmentation result possibly reserving forged regions. As an unsupervised image segmentation approach, our approach improves the segmentation performance from the view of forged object extraction. Modules1.

**Image Preprocessing** The image division operator normally takes two images as input and produces a third whose pixel values are just the pixel values of the first image divided by the corresponding pixel values of the second image. Many implementations can also be used with just a single input image, in which case every pixel value in that image is divided by a specified constant. The pixel values are actually vectors rather than scalar values (e. g. for color images) than the individual components (e. g.

red, blue and green components) are simply divided separately to produce the output value. The division operator may only implement integer division, or it may also be able to handle floating point division. If only integer division is performed, then results are typically rounded down to the next lowest integer for output. The ability to use images with pixel value types other than simply 8-bit integers comes in very handy when doing division. 2.

**Edge Classification**The given image is represented in scale-space by repeatedly smoothing with a Gaussian filter of increasing size. 12 levels in scale space are extracted. Then, the features' locations and scales are decided by using scale-adapted Laplacian of Gaussian (LoG), which can indicate gradient changes and corners in the image. For the LoG filter, the output of the standard LoG filter is convolved with a scale-adapted Gaussian filter, whereas a similar approach is adopted for the Gaussian filter by using a multi-scale Gaussian operator. Likely candidates for feature points are selected based on having certain values resulting from the LoG and Harris filters. For points having a Harris filter response greater than a prespecified threshold, we sort the points in decreasing order of LoG filter response.

The  $N$  points with the maximum responses (subject to meeting exclusion zone criteria) are selected for signature extraction. An exclusion zone of  $M$  pixels is used around each feature to maintain a minimum spatial distance between two features. This is important because it is quite likely that points showing the highest response to the filters tend to come from the same objects or regions, and we wish to avoid clustering of features in certain areas of the image. **Feature Extraction:** A circular region around each feature point (with a radius dependent on the scale) is scaled to a radius of 32  
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pixels, allowing for robustness to scale changes. This region is then subjected to the trace transform, which is a generalization of the Radon transform.

It generalizes the Radon transform by allowing for various functionals (in addition to the integral used in the Radon transform) to be applied over straight lines in the circular region. By a proper choice of a functional, invariance to rotation and scaling can be achieved. The trace transform is computed by drawing samples (indexed by  $t$ ) along lines parameterized by distance. RDP Model Generation In the RDP model, the straight world line is first projected to a great circle on the viewing sphere and then projected to a conic on the image plane. This projection, where the purple lines denote the projection of a straight world lines. The conic is fitted from the projected points of purple world line. The points represent two endpoints and one midpoint of the candidate line and are back-projected into points, respectively.

The points define a great circle, which is projected to the straight line in the space with the center of the viewing sphere. In contrast, the points lie on the forgery line, which could be presented as a conic section on the forgery object. The three points are back-projected to points on the viewing sphere, which defines another circle. Note this circle is not a great circle on the viewing sphere, because the forgery line is not satisfying this geometric constraint any more.

In other words, the circle generated by the forgery line determines a plane section, which cuts the viewing sphere without passing the center of the

view sphere, as shown as the red dotted circle . Thanks to this constraint of line, there are two effective bottom-up cues, the volume cue and the distance cue, which could be used to distinguished the forgery line. Volume Cue Extraction With the geometrical constraint, if three points on the image plane are projected from the straight world line, their back-projected points on the viewing sphere follow the geometrical constraint where Volume is the volume of tetrahedron made up by the center of viewing sphere and points of the great circle , as shown as the purple shadow. Statistically, the forgery line is highly unlikely to satisfy this geometrical constraint, as the blue shadow.

So the volume cue is defined as a bottom-up cue where is the length of the forgery line in the image. the curves of the volume cue of each candidate line with different virtual focal length of the RDP model, where the volume cues of original lines are close to zero and the cues of forgery lines are more likely to be away from the zero. But in the experiments, the volume cue of the forgery line, which locates away from the image center, is not distinguished clearly with the cues of original lines, such as the right-most candidate line in the second sample. Note that with the virtual focal length , the RDP model degenerates and all the distortion values equal to zero, because the projective transformation of the Step 2 is invalidated and the incidence angle of every pixel vanishes identically.