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Contrast enhancement influences the detection of gradient based local invariant features and the matching of their descriptors ☆

Stefan G. Stanciu [a,b,*], Denis E. Tranca [a], Dinu Coltuc [c]

[a] Center for Microscopy – Microanalysis and Information Processing, University "Politehnica" of Bucharest, 313 Splaiul Independentei, Sect. 6, 060042 Bucharest, Romania
[b] Light Microscopy and Screening Center, Swiss Federal Institute of Technology ETH Zurich, Schaffmatstrasse 18, Zurich, Switzerland
[c] Electrical Engineering Department, Valahia University Targoviste, Bd. Carol I, Nr. 2, Romania

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ABSTRACT

Contrast enhancement (CE) plays an important role in digital photography, medical imaging or scientific visualization, compensating for deficient dynamic range aspects. Our experiments show that CE via histogram modification influences the detection of gradient based local invariant features (LIF) and the matching of their descriptors. We bring evidence that the number of keypoints that can be automatically extracted by gradient based detectors increases with CE, and that matching gradient based keypoint descriptors extracted from image sets processed by CE is negatively affected in terms of Precision–Recall. We observed the effects of several classical and state-of-the-art CE methods on two widely used LIF detection/description techniques: Scale Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF).

1. Introduction

Contrast enhancement (CE) plays an essential role in a wide range of image processing applications belonging to various fields such as digital photography, medical imaging, scientific visualization and others. Typical reasons behind the need for CE consist in reduced dynamic range (the ratio between the maximum and minimum measured light intensities) due to the characteristics of the imaging device, insufficient expertise of the operator in charge of the image acquisition tasks or due to imbalanced illumination conditions.

In the past couple of decades a solid body of work has been deployed for developing various CE strategies and methods, e.g. [1–17]. The great majority of CE methods focus on histogram modification (HM), also known as histogram modeling. Basically, HM refers to a class of image transforms that aim to modify images so that their histogram meets a desired shape or desired characteristics [18,19]. A prominent example is histogram equalization, which is meant to spread image gray levels over the entire scale and to allocate an equal number of pixels to each gray level. Besides visual enhancement for digital photography, HM has also been employed to date in the frame of various other applications such as brightness compensation in optical microscopy data sets [20–22], correction of uneven exposure and maximization of the number of fringes in interferometry [23], biometric face recognition [24], coherence analysis enhancement [25], medical image enhancement [26,27] and many others.

In parallel with significant developments reported in the field of digital image processing, the computer vision field has witnessed as well remarkable advances over the past twenty years. Among other high-impact topics, the scientific community working in this latter domain had placed a strong focus of attention in the past decade on the detection of local invariant features (LIF) and on their description [28–31]. LIF detectors aim to identify image features that can be repeatably recognized in different instances of an imaged scene or object, such as images collected under different acquisition parameters or under different viewpoint perspectives. LIF description strategies aim to encapsulate invariant information corresponding to detected LIF in a descriptor vector, so that descriptor vectors calculated for corresponding image features extracted from different image instances of the same object or scene can be easily matched based on their similarity. LIF represent popular computer vision tools that have been successfully used to date in a multitude of applications oriented for tasks such as image

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* Corresponding author at: Center for Microscopy – Microanalysis and Information Processing, University "Politehnica" of Bucharest, 313 Splaiul Independentei, Sect. 6, 060042 Bucharest, Romania.

E-mail address: stefan.stanciu@cmmip-upb.org (S.G. Stanciu).

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retrieval [32,33], tracking [34,35], wide baseline matching [36,37], image stitching [38,39], image based localization [40–42], medical image classification [43–45] and many others. Among the numerous methods for LIF extraction and description that have been reported so far, the Scale Invariant Feature Transform (SIFT) [46] and Speeded-Up Robust Features (SURF) [47] represent two of the most preferred choices because of their high accuracy and robustness, relatively low computation time and the availability of open-source implementations.

The robustness of LIF detection and description depends on the properties of the object image. However, to date only few studies have addressed the impact of image pre-processing techniques routinely used for image enhancement (or for other tasks) over LIF detection and description. For example, in a project report Tsai [48] brought evidence that SURF based image matching can be enhanced using a cascade of 2-D Pre-processing tasks, Kalia et al. [49] have showed that CE improves feature detection repeatability in the case of several state-of-the-art detectors, and that image scaling strategies hold significant potential for accelerating LIF based image matching, while Campos et al. [50] concluded that Gabor filter preprocessing does not improve the performance of the SIFT algorithm in the case of a specific ocular recognition application that they have addressed. The results that we present shed more light in this poorly explored area, showing that CE via HM comes accompanied by side effects in respect to the detection and matching of LIF; more precisely we show that CE via HM yields an increase in the number of SIFT and SURF keypoints that can be automatically extracted from a digital image, and that at the same time a matching procedure of SIFT and SURF descriptors is affected in terms of Precision–Recall if the support image set is previously processed for CE. In most computer vision applications based on LIF, these are detected independently in each image (or extracted from fixed locations) and then the LIF of one image are matched against the LIF of other images by direct or indirect comparisons of their respective feature descriptors, see Fig. 1. We consider our findings to be important because the core of such aforementioned applications is based on determining interest point correspondences between individual image pairs (or between an image and a class of images) and fluctuations in the number of extracted keypoints or in the robustness of the LIF descriptor have direct implications for the outputs and performance of the method.

We demonstrate how CE affects SIFT and SURF detection and matching for ten CE methods:

- Classical global histogram equalization (GHE) [18].
- Histogram normalization (HN) by exact histogram specification [15].
- Adaptive Gamma Correction With Weighting Distribution (AGCWD) [3].
- Histogram Modification Using Bilateral Bezier Curve (BBC) [4].
- Contextual and Variational Contrast Enhancement (CVC) [9].
- Contrast Enhancement Based on Layered Difference Representation of 2-D Histograms (LDR) [5].
- Non-parametric Modified Histogram Equalization for Contrast Enhancement (NMHE) [6].
- Range Limited Bi-Histogram Equalization for Image Contrast Enhancement (RLBHE) [7].
- Histogram Modification Framework for Image Contrast Enhancement (WAHE) [12].
- Local Histogram Specification (LHS).

The paper is organized as follows: In Section 2 we present the employed methods, in Section 3 we present the achieved results and discuss their causes and implications, while in Section 4 we outline our conclusions. The structure of Sections 2 and 3, which include several sub-sections, is presented in their first part.

2. Methods

This section is structured as follows: in Section 2.1 we highlight the main concepts of SIFT and SURF, the two LIF detection/description methods that we address; in Section 2.2 we present the typical Nearest-Neighbor strategies used for matching LIF descriptors; in Section 2.3 we briefly introduce and discuss the concepts of the ten CE methods that we have tested against SIFT and SURF, while in Section 2.4 we present the image set that we used as support.

2.1. SIFT and SURF

Our experiments are aimed at demonstrating the effects of classical and state-of-the-art CE methods on the outputs of two widely used computer vision tools, SIFT [46] and SURF [47]. Both techniques belong to the family of scale invariant feature detectors, and in both SIFT and SURF local feature detection is achieved by analyzing an input image at different scales in order to find repeatable characteristic structures independently of their actual size in an image. Both algorithms use multiscale detection operators to analyze the scale space representation of an image for LIF extraction and include as well methods for the description of the detected LIF.

In SIFT the keypoint descriptor is a histogram representation that combines local gradient orientations and magnitudes from a certain neighborhood around a keypoint. More precisely, the descriptor is in fact a 3D histogram of gradient location and orientation, where location is quantized into a 4×4 location grid and

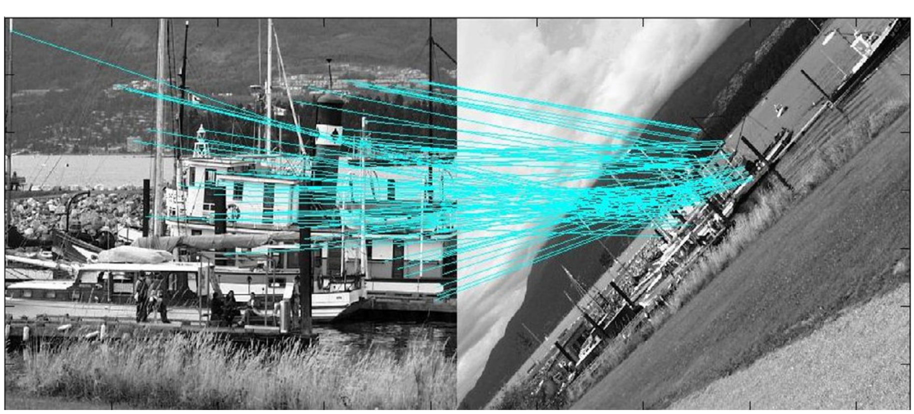

Fig. 1. Example of matched local features extracted from two images of the same scene collected under different zoom and rotation conditions. SIFT features are detected in both images, and are matched in the absence of any *a priori* information by using their assigned descriptors. The blue lines connect the matched features. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)