New shadow detection and removal approach to improve neural stereo correspondence of dense urban VHR remote sensing images

Ehlem Zigh1*, Mohammed Faouzi Belbachir2, Mohammed Kadiri3, Mohammed Djebbouri4 and Belkacem Kouninef6

1Laboratory of research in applied ICT (LARATIC), National Institute of Telecommunications and Information Technologies and Communications, B.P 1518, el M’naouer, Route de sénia, 31000, Oran, Algeria
2University of Sciences and The Technologies of Oran Mohamed Boudiaf USTOMB, B.P 1505, El M’naouer, Bir el djir, 31000, Oran, Algeria
3University Mustapha Stambouli, 29000, Mascara, Algeria
4University Djillali Liabès, 22000, Sidi-Bel-Abbes, Algeria
*Corresponding Author, e-mail address: zigh_ehlem@yahoo.fr

Abstract
Shadows cause problems in many remote sensing applications like images segmentation, objects extraction and stereo vision. This paper presents a new and an automatic approach to detect and remove shadows from pair of dense urban very high resolution (VHR) remote sensing images. The main contribution of this paper is twofold. First, a proposed approach is efficient to restore objects hidden by shadows, second, it improves a stereo matching process. We have chosen to operate on Ikonos pairs as an example of urban remote sensing images, for that, shadow detection is achieved using a new technique of property based method, operating directly in red, green and blue colour space (RGB). Shadow removal proposed technique aims to produce a needed amount of light to the shadow regions by multiplying the shadow regions by constants, after that, the shadow edge correction is applied to reduce the errors due to diffusion in the shadow boundary. Once pair of shadow free images is recovered, we apply a stereo matching process using a Hopfield neural technique in order to find homologous regions. Our results from different urban pairs show the effectiveness, the simplicity and the fastness of the proposed approach to reveal details hidden by shadows and to obtain a high stereo matching rate.

Keywords: Neural stereo correspondence, remote sensing, shadow detection, shadow removal, Ikonos images.

Introduction
In the last years, both very high resolution (VHR) urban remote sensing images and aerial images show very fine details of features such as buildings, roads, cars and vegetation [Maglione et al., 2014], however, the amount of shadow and occlusion increases with the spatial resolution. Shadow is an inevitable natural phenomena which is usually cast
by elevated objects like buildings, bridges, towers, and it is necessary to reduce or to compensate its effect in order to get information we need according to the application aimed at. In this paper, we are interested in stereo matching of buildings of urban areas located in Ikonos VHR images, the proposed method constitutes of an extension, of the one we have proposed in Zigh and Belbachir [2012], to occluded buildings. So, to obtain accurate results, we have to overcome shadow issues.

Shadow detection and removal methods work together to remove shadows [Krishna et al., 2012]. One of the most important reviews of shadows detection techniques were cited in Andres et al. [2012], Al-Najdawi et al. [2012] and Shahtahmassebi et al. [2013]. Andres et al. [2012] have reviewed recent methods for moving objects in video sequences, Adeline et al. [2013] have presented a study of shadow detection methods for single very high resolution aerial images. From that, we can categorised shadow detection method for very high resolution remote sensing images into four main classes: machine learning methods, physics based methods, model based methods and property based methods.

In the first class, Martel-Brisson and Zaccarin [2005], have used Gaussian mixture model as an unsupervised method to classify shadowed regions, Levine and Bhattacharyya [2005] have used Support Vector Machine (SVM) to classify shadow boundaries after segmentation and Lalonde et al. [2010], have proposed a supervised shadow classification using a conditional random field. These methods require reference samples to train the classifier and/or are generally computationally expensive.

In physics based methods, shadow detection algorithms generally use material reflectances, they take into consideration the illumination and the atmospheric conditions, and derive some physical properties of material. There are few published papers using this class [Adler- Golden et al., 2002; Richter and Müller, 2005] because of the lack of this additional information.

Model based methods need an accurate 3D model or an atmospheric illumination conditions to determine where shadows are located on the image [Adeline et al., 2013]. So, it is performed directly on radiance data. Using digital surface models (DSM), several geometrical methods for shadow detections have been published in literature, like Rau et al. [2002], whom use Z-buffer technique with DSM data and multi-view ortho-photos, more recently, Tolt et al. [2011] employ a straight forward line-of-sight analysis with a very accurate DSM combined with SVM supervised classification.

The last class called property based methods doesn’t require any priori information because it can be applied directly to raw data based on some specific properties like chromaticity and intensity. Paul Dare [2005] has detected shadow from panchromatic Ikonos images by thresholding at a predetermined level and post processing the segmented regions, Tsai [2006] has exploited the properties of shadows in chromaticity, it was applied in several invariant colour spaces including hue-saturation-value (HSV), hue-saturation-intensity (HSI), hue-chroma-value (HCV), luma-in phase-quadrature (YIQ) and luma-blue difference-red difference chroma components (YCbCr) models, Arévalo et al. [2008] have exploited both a shadow invariant colour component and edge information to detect shadow in Quickbird images. More recently, Krishna et al. [2012] have detected shadow by considering the HSV colour space using Otsu’s method for thresholding.

Almost all shadow detection scientific researches cited above were applied on very high
resolution single images (aerial or satellite images). Concerning our research, we have to mention three main points:

- We apply shadow detection for stereo VHR remote sensing images, it is considered as a pre processing stage to another one, so it must be computationally fast and the use of machine learning methods isn’t advised in our case;
- We don’t have additional data, like reference images, atmospheric conditions and DSM, therefore, physics and models based methods are not required;
- We have observed from the property based methods that the choice of features has greater impact on shadow detection results.

From that, we propose a new fast shadow detection technique using RGB colour space and two features: spectral (intensity) and spatial (shape of shadows).

Once shadows areas are located, they can be removed. There exists several shadow removal techniques, each one often depends on the shadow detection method used beforehand. Nevertheless, we can distinguish two main shadow removal methods [Feng and Gleicher, 2008]: the first one is the zeroing gradient applied in the penumbra (boundaries of shadow) followed by image reconstruction step [Finlayson et al., 2002; Weiss, 2001], like Finlayson et al. [2006] whom achieved the shadow removal in three stages: a 1D shadow-free illumination invariant image is created, from this, a 2D colour representation is derived and then a 3D shadow-free color image is generated, the shadow edges are finally corrected by in-painting. In Feng and Gleicher [2008], a shadow free image is reconstructed by reintegrating using poisson equation. Finlayson et al. [2009] proposed that shadows can be removed by minimizing entropy and, more recently, Qiang and Chee-Hung [2013] used the fisher linear discriminate to produce the invariant images and reintegrated the derivative filter outputs to generate shadow free images.

The second class of methods consists of removing shadow by multiplying a suitable scalar to the shadow pixels. We can cite a scientific research of Almoussa [2005] who minimized an energy function to obtain this scalar. In the same class, Murali and Govindan [2013] removed shadow by multiplying R, G and B channels of the shadow pixels using appropriate constants.

Most of the works in the first class of shadows removal methods cited above, need multiple images, calibrated camera and user intervention with brush tool to specify the shadow boundary, also, reintegrating using poisson equation is time intensive.

The second class includes simpler methods than those in the first one. Therefore, we have been inspired from an energy minimization concept applied in Almoussa [2005], to propose a new shadow removal method which consists in minimizing the existing energy between shadowed and illuminated (unshadowed) areas, to find three suitable coefficients related to the three image components R, G and B.

Our main contribution in a proposed removal method is the insertion of some filters to improve a shadow removing, particularly in penumbra area.

A proposed shadow removal method is innovative in VHR urban remote sensing images. In this field, where a phenomena is so complicated because it exists in dense and variable areas, we feel a high contribution of our method to improve a result of buildings stereo matching process.
The considered shadows
Shadows occur when objects totally or partially occlude direct light from a source of illumination. Shadows can be divided into three classes: cast, self and boundaries (Fig. 1). These classes can be considered as three kinds of usefulness shadow (Fig. 2). A cast shadow is projected by the object in the direction of the light source, a self shadow is the part of the object which is not illuminated by direct light and boundaries consist of the edge of shadow called penumbra.

Most of the proposed methods presented in the remote sensing field only deal with cast shadows [Arévalo et al., 2008]. In this paper, our challenge is to deal with both cast and self shadow, also, we are interested in correcting penumbra areas.

We mention that we have to treat only large surfaces of shadows called “usefulness shadows”, because the smallest ones situated outside usefulness shadows are considered “helpful” for a next processing stage: buildings extraction, we called them “useful shadows” (Fig. 1).

We notice that we predefine this classification of shadows into “usefulness” and “useful” shadows (Fig. 2).

Description of the proposed method
Figure 3 shows the flowchart of the proposed shadow detection and removal method used to improve buildings stereo matching process. A method used to put in correspondence buildings from the pair of mages has been applied previously by Zigh and Belbachir [2012].
Shadow detection step
We are interested in this paper by removing large areas of shadows called usefulness shadows, for that, we should detect these shadows beforehand.
Keeping an initial colour space of our pairs of images (RGB), a proposed shadow detection method is based on the spectral and spatial information of image, it consists of Otsu thresholding algorithm which calculates an optimal threshold that minimizes the intra-class variance, after that, some spatial filters are added in order to preserve only the usefulness shadows.
So, firstly, the algorithm separates shadows (cast and self-shadows) from non-shadows by thresholding at a predetermined level according to an equation:

\[
I^{\text{umbra}}(i,j) = \begin{cases} 
1 & \text{if} \ I(i,j) \leq l \\
0 & \text{if} \ I(i,j) > l
\end{cases}
\]

With:
\(I^{\text{umbra}}(i,j)\): image after Otsu thresholding;
\(I(i,j)\): initial image;
i=1…N: rows number;
J=1….M: columns number;
l: corresponding threshold.
As a result, we obtain a binary image with black shadowed areas corresponding to zero pixels (Fig. 3b). However, Otsu algorithm doesn’t offer the opportunity to extract only large shadowed regions (usefulness shadows), for that, in the second phase, the useful regions considered as artefacts are deleted using the following spatial filters:

a. Filtering areas outside the usefulness shadows (these areas are called useful shadows): each black or low brightened object existing outside the usefulness shadows is detected as a shadow which makes confusion (Fig. 4b). This object can be a small surface of shadow that is useful for us (useful in building extraction step). For that, we apply a morphological closing filter to delete it (Fig. 4c);

b. Filtering inside the usefulness shadows: white or high brightened object existing in the usefulness shadows couldn’t be detected as a shadowed object (Fig. 4b), so, it will be deleted using a median filters (Fig. 4c).

As we detect the usefulness shadows regions that can be cast or self (Fig. 4c), we have to remove them in the next step.

**Figure 4 - Usefulness shadows detection.**

**Shadow removal step**

We propose a new shadow removal method, it is based on an energy minimization concept followed by a penumbra correction technique.

As we assume that the hidden regions under the usefulness shadow achieve almost the same illumination as the nearest non shadow regions [Murali and Govindan, 2013], we need to compute the average value for each colour (R, G and B) inside and outside shadow regions, so, the constant light is a three-component vector, one component for each light: red, green, and blue. Denote it by \( \tilde{c} = (c_R, c_G, c_B) \). The value of \( \tilde{c} \), once added to the shadow region, must minimize the norm of the different between the average light inside and the average light outside the shadow region. Therefore, our energy function can be:

\[
E(\tilde{c}) = \left[ (c_R \mu_R^R - \mu_{\text{out}}^R)^2 + (c_G \mu_G^G - \mu_{\text{out}}^G)^2 + (c_B \mu_B^B - \mu_{\text{out}}^B)^2 \right] \quad [2]
\]
with:

\( \mu^R \): The average red light inside the shadow region;

\( \mu^R_{out} \): The average red light outside the shadow region;

\( \mu^G \): The average green light inside the shadow region;

\( \mu^G_{out} \): The average green light outside the shadow region;

\( \mu^B \): The average blue light inside the shadow region;

\( \mu^B_{out} \): The average blue light outside the shadow region.

To find \( \tilde{c} \), we compute the partial derivatives of \( E(c) \) and set each one of them to zero:

\[
\begin{align*}
\frac{dE}{dc^R} &= 2.0 \left( c^R \mu^R - \mu^R_{out} \right) = 0 \quad [3] \\
\frac{dE}{dc^G} &= 2.0 \left( c^G \mu^G - \mu^G_{out} \right) = 0 \quad [4] \\
\frac{dE}{dc^B} &= 2.0 \left( c^B \mu^B - \mu^B_{out} \right) = 0 \quad [5]
\end{align*}
\]

solving these three equations gives:

\[
\tilde{c} = \left( \frac{\mu^R_{out}}{\mu^R}, \frac{\mu^G_{out}}{\mu^G}, \frac{\mu^B_{out}}{\mu^B} \right) \quad [6]
\]

We notice that the shadow detection and removal method proposed above, was applied on many urban pairs of images (around thirty pairs), we choose to illustrate in this paper, only the results concerning the two most complicated shadowed urban scenes. As an example, we illustrate below a result of shadow removal method for one image (Fig. 5). Here, an obtained coefficient \( \tilde{c} \) according to equation (6) is \( \tilde{c} = (4.8870, 5.0634, 3.9041) \), this one has been calculated using the following matlab code:

```matlab
Ain(:,:,1) = (1 - shadow) .* I(:,:,1);
Ain(:,:,2) = (1 - shadow) .* I(:,:,2);
Ain(:,:,3) = (1 - shadow) .* I(:,:,3);
Aout(:,:,1) = shadow .* I(:,:,1);
Aout(:,:,2) = shadow .* I(:,:,2);
Aout(:,:,3) = shadow .* I(:,:,3);
sumIN = reshape(sum(sum(Ain )),1,3);
sumOUT = reshape(sum(sum(Aout)),1,3);
Vin = sumIN/sum(sum(1 - shadow));
Vout = sumOUT/sum(sum(shadow));
c = Vin./Vout.
```
According to the obtained image (b) in Figure 5, we notice that the shadow is well removed, so, the hidden objects are recovered. The only inconvenient is an over-illumination towards the boundaries of shadow.

Boundary of shadow is one kind of edges, so, it can be defined as an abrupt local change of intensity in an image. In a shadow removal method cited above, we multiply shadow boundary by a coefficient “c” (see Equation 6 above), which creates an over-illuminated shadow area (Fig. 5b and Fig. 6b).

To overcome this issue, we propose a new penumbra correction technique which consists of two parts: penumbra detection and penumbra smoothness.

a. Penumbra detection: boundaries of shadow are detected using a binary image (obtained from shadow detection step detailed in paragraph 3.1). After that, a Canny filter is applied on this binary image, and in order to raise the thickness of shadow boundaries, morphological dilation is used. A final result of penumbra detection step is illustrated below on Figure 6c;

b. Penumbra smoothness: it is achieved using a median filter (5*5), considered as a non linear low pass filter which aims to reduce the amount of intensity variation between each penumbra pixel and its neighbours (Fig. 6d).
The proposed method in the buildings stereo matching process

The entire process was tested over the pair of stereo sample images generated by IKONOS 2 satellite data and used previously in Zigh and Belbachir [2012]. We have only one pair of stereo images and we are interested in building stereo matching application in shadowed areas, for that, we choose only shadowed sub pairs (portions) acquired under different sun elevation angles and covering urban areas with elevated buildings. These sub pairs are selected using Paint tool.

To evaluate the performance of the proposed approach, the training set includes thirty shadowed sub pairs, we illustrate in this paper the results concerning only two typical urban sub pairs where significant shadow regions appear. We notice that the shadow existing in the second original sub pair (Fig. 8) is larger and more complicated than that in the first original sub pair (Fig. 7).

![Figure 7 - The first original sub pair.](image)

![Figure 8 - The second original sub pair.](image)

The proposed shadows detection and removal method is applied to improve the building stereo matching process proposed previously in Zigh and Belbachir [2012]. This stereo correspondence is a neural method, the quality of its result depends strongly on the fuzzy buildings extraction step done beforehand [Zigh and Belbachir, 2012]. To demonstrate the usefulness of the proposed shadows detection and removal method, we apply stereo
matching process firstly on the original pairs (shadowed pairs) and secondly on the recovered shadowed free pairs.

**Results of stereo matching process on the original pairs (shadowed pairs).**
Firstly, we show below the results of stereo matching process applied on the first original shadowed pair of images.

![Figure 9 - Stereo matching process on the first original sub pair (shadowed sub pairs). (a), (b) Original right and left images; (a1), (b1) Fuzzy buildings extraction from right and left images; (a2), (b2) Labeling of extracted buildings from right and left images; (a3), (b3) Neural stereo matching result.](image)

As it is illustrated above, fuzzy buildings extraction step gives us a good segmentation of regions of interest (buildings), however, it doesn’t allow a same number of regions in each image for two main reasons: Firstly, the difference of capture conditions from right to left image has an effect on regions positions, as a result, some regions in the left image haven’t homologous in the right one (Fig. 9a2, b2) such as regions 18 and 26 in Figure 9b2. Secondly, the shadow hides many regions, so they can’t be extracted, like region labelled 37 in the left image which hasn’t got homologous in the right image (Fig. 9b2, a2). In total, we obtain only 25 regions in the right image (Fig. 8a2) and 43 regions in the left one (Fig. 8b2) (see Tab. 1). The result of this step (buildings extraction) has a direct influence on a next one called neural stereo matching process. So, an obtained matching rate is 44% in the right image and 25.58% in the left one (see Tab.1), we have only one ambiguous region relative to nearest areas.

We notice that a neural stereo matching applied technique is based on a Hopfield network whose nodes constitute of the defined assumptions (the possible regions correspondence), and the connections between them represent the new constraints, including geometric and
photometric regions properties: surface, elongation, perimeter, colour and gravity centre coordinates [Zigh and Belbachir, 2012]. The optimization problem is solved by minimizing an energy function, so, an update of each neuron state is done in order to perform the network evolution and then allowing it to settle down into a stable state. The stable state represents the best solution (each neuron represents a possible correspondence between a right region and a left one).

**Table 1 - Neural stereo matching method applied on original sub pairs (shadowed sub pairs).**

| Stereo shadowed images | First sub pair | Second sub pair |
|------------------------|---------------|-----------------|
| Number of matched pairs of regions in the left image | 11 per 43 | 11 per 43 |
| Number of matched pairs of regions in the right image | 11 per 25 | 11 per 35 |
| Number of ambiguous regions (Left, Right) | (01, 01) | (02, 01) |
| Matching rate (left image, right image) | 25.58%, 44% | 25.58%, 31.42% |
| An average matching rate | 34.79% | 28.5% |

Secondly, we apply stereo matching process on the second pair of images, this one can be considered as one of the most complicated shadowed existing VHR remote sensing pairs.

*Figure 10 - Stereo matching process on the second original sub pair (shadowed sub pairs). (c), (d) Original right and left images; (c1), (d1) Fuzzy buildings extraction from right and left images; (c2), (d2) Labeling of extracted buildings from right and left images; (c3), (d3) Neural stereo matching result.*
We notice that shadow surface varies from the left to the right image covering the same scene. This variability increases according to shadow complexity which is more prevalent near sky scrapers (Fig. 10c, d). From there, all shadowed buildings couldn’t be extracted, we clearly see on Figure 10c2, d2 that they are fused with a background. We have obtained from the fuzzy buildings extraction step, 35 regions in the right image and 43 regions in the left one. As a result, shadowed buildings are not matched, a neural stereo matching rate in the right image is smaller than that obtained in the first sub pair (31.42% compared to 44%) with three ambiguous regions (regions labelled 3,6,7). Concerning a left image, we have obtained a same stereo matching rate 25.58% in the two sub pairs, but we have three ambiguous regions in the second sub pair (regions labelled 3,7,6) (Tab. 1).

**Results of stereo matching process on the recovered shadowed free pairs**

Now, we apply a proposed shadow detection and removal method in the beginning, in order to detect hidden regions which will be extracted. As it was indicated previously (in section 2 - The considered shadows-), we are interested in recovering only a large shadow areas (usefulness shadows), the smallest ones situated outside usefulness shadows are helpful in our case, so, we can easily see on Figure 11aa1 that they were been merged with a background. Therefore, a result of a fuzzy buildings extraction step is efficient. Much more regions are obtained compared to first case (first shadowed sub pairs in Fig. 9), there are 33 regions in the right image and 46 regions in the left one. This buildings extraction result has a direct and a positive impact on a neural stereo matching process.

![Figure 11 - Stereo matching process on the recovered shadowed free first sub pair. (aa), (bb) Recovered shadowed free right and left images; (aa1), (bb1) Fuzzy buildings extraction from right and left images; (aa2), (bb2) Labeling of extracted buildings; (aa3), (bb3) Neural stereo matching result.](image-url)
An example of one of totally hidden buildings recovering is a pair of regions labeled 12 in Figures 11aa3 and bb3. An example of partially hidden buildings recovering is a pair of regions labeled 16 in the same Figure 11 aa3 and bb3. As a result, we obtain an interesting stereo matching rate, it is 63.63% in the right image and 45.65% in the left one (Tab. 2), it corresponds to an average improvement of 19.85% more than the first stereo matching case (first shadowed sub pair).

### Table 2 - Neural stereo matching method applied on recovered shadowed free pairs.

| Stereo recovered shadowed free images | First pair | Second pair |
|--------------------------------------|------------|-------------|
| Number of matched pairs of regions in the left image | 21 per 46 | 18 per 56 |
| Number of matched pairs of regions in the right image | 21 per 33 | 18 per 50 |
| Number of ambiguous regions (Left, Right) | (01, 01) | (01, 01) |
| Matching rate (left image, right image) | 45.65%, 63.63% | 32.14%, 36% |
| An average matching rate | 54.64% | 34.07% |

After that, we apply stereo matching process on the second recovered shadowed free sub pair. Obtained results are illustrated below.

Figure 12 - Stereo matching process on the recovered shadowed free second sub pair. (cc), (dd) Recovered shadowed free right and left images; (cc1), (dd1) Fuzzy buildings extraction from right and left images; (cc2), (dd2) Labeling of extracted buildings. (cc3), (dd3) Neural stereo matching result.
Concerning this dense urban pair of images having one of the most complicated and expanded shadow, a proposed shadow detection and removal approach allows an interesting recovering of shadow affected objects, we can show for example recovered regions 8 and 15 (Fig. 12cc3 and dd3) which were totally hidden in original pair of images (Fig. 10c1 and d1). Another example concerning a partially hidden regions includes region labelled 2 (Fig. 10c1 and d1), it is completely restored after shadow treatment (Fig. 12cc3 and dd3).

As a result, we obtain 56 extracted regions in the left image and 50 extracted regions in the right one (Tab. 2), let’s remember that we have detected before the application of shadow detection and removal algorithm only 43 extracted regions in the left image and 35 extracted regions in the right one (Tab.1).

A result of fuzzy buildings extraction step influences positively on neural stereo matching process, so, we obtain a matching rate equal to 32.14% for left image and 36% for right image.

**Computational time of the improved buildings stereo matching process**

A computational time is almost proportional to the size of input images (i.e original images) and the applied algorithm. In our study, during each program execution, the proposed algorithm is applied on the right and the left images at the same time, having each one a size of 208*287 pixels. The program is executed using an Intel Core I3 machine with a 64-bit operating system and 4 GB RAM.

We have shown above (Tabs. 1 and 2) that the ability of the proposed shadows detection and removal approach to reveal details covered by shadows influences directly on the neural stereo matching result, so, the improved buildings stereo matching process is more accurate and its rate is raised.

To proclaim the fastness of the improved buildings stereo matching process, we calculate a computational time with and without shadows processing. So, for the first pair of images, without shadows detection and removal: a total time cost is 09.04 seconds (4.33 seconds for a stereo matching step), and with shadows detection and removal step: a total time cost is 12.62 seconds (6.93 seconds for a stereo matching step).

For the second pair of images, without shadows detection and removal step: a total time cost is 13.13 seconds (6.74 seconds for a stereo matching step), and with shadows processing step: a total time cost is 17.62 seconds (7.13 seconds for a stereo matching step).

We notice that about a half of total time processing is consumed by a neural stereo matching step, this time is needed by neurones to reach a stable state. Nevertheless, shadow detection and removal processing uses few seconds which could be very promising in large area of applications (because the other half of time processing includes: images readings and plotting + shadows processing+ regions labelling).

The second pair of images includes one of the most complicated and expanded shadows, so, it needs more computational time to give appropriate result.

But, in general, with a memory space of 2.10 GB and a time processing equal to 17.62 seconds at maximum in a most complicated case, a computational time necessary to improve the buildings stereo matching process is considered as low, it could be reduced much more using a faster processor and a bigger RAM size as 8GB.
Conclusion
A new method to detect and remove shadows from the pairs of RGB very high resolution remote sensing images is proposed. We have chosen to operate on Ikonos images as an example because they can be considered as one of the most prevalent shadowed remote sensing images.
A primary goal of the proposed method is to deal with cast, self and boundaries of usefulness shadows, for that, an hybrid detection method which combines spectral and spatial information is done, it doesn’t require any priori information and it operates directly on RGB colour space without any spaces conversions as it has been done in Murali and Govindan [2013] and Krishna et al. [2012]. It is simple and efficient. It is clear that the not conversion of the color space allows a short time processing. After that, shadow is removed using an energy minimization method, our main contribution in a proposed removal method is the insertion of some filters to improve shadow removing, particularly in penumbra area. This removal method is automatic and efficient.
A second goal of a proposed shadow detection and removal method is to improve a building neural stereo matching process in complex urban environment. In stereo images, although surfaces of shadows change from left to right image covering the same scene, we notice that shadows in the recovered images obtained from a proposed method are either considerably attenuated or effectively removed, from that, new pairs of regions (buildings) appear, as a result, we obtain an interesting improvement of stereo matching rate and a good reduction of ambiguous regions. Experimental results show that the stereo matching method [Zigh and Belbachir, 2012] applied on the recovered shadowed free pairs gives better results than the same one applied on the original pairs (shadowed pairs). So, we can conclude that the whole method in this paper is simple, fast and efficient.
The application of the proposed shadow detection and removal method isn’t limited to the stereo matching of buildings, it can easily be applied to restore and to put into correspondence other kind of regions like cars or facets of buildings.

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