Towards Enriching the Estimation of Stone Degradation through Computer Vision Analysis

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Abstract

Black crusts on stone surfaces, mainly composed of gypsum crystals, not only aesthetically affect the stonework but also cause further decay. Appropriate conservation methods should non-destructively detect the pollutant type and extent. In this paper, we propose a computer aided diagnostic method for automatically detecting deterioration patterns on black crusts. The proposed non-destructive method can be applied in situ. The applied detection process quantifies the alteration due to weathering and assesses the efficiency of several chemical cleaning methods. The detection process is based on a combination of Gaussian and morphological filtering. The results of both methods are fused via a Conditional Thickening operation in order to obtain reliable results concerning the spatial density, topology and extent of the deterioration patterns, while preserving their extent and shape characteristics. The algorithm is tested with a series of images depicting the corrosion state on marble surfaces. Decay patterns, classified by their chemical composition as black and white particles, are significantly decreased after the chemical cleaning, as indicated by the applied algorithmic approach. The corrosion alteration after cleaning is quantified in terms of robust statistical metrics expressing the extent, spatial density and thickness of the crusts.

Keywords: black crusts, blob detection, shape preservation, decay quantification

1 Introduction

During the last decades there has been a growing concern about the changes in air quality and the effects on the deterioration of stone monuments. The factors leading to stone degradation can be distinguished into two main categories according to their origin. More specifically, natural weathering and anthropogenic activities induced stone decay.

Airborne pollutants, such as SO_2, NO_x and O_3 are gaseous components which directly react with the stone surface producing harmful salts. The latter, either crystallize out within the stonework resulting to a physical damage, or they are washed away leading to a loss of the stone material. Except for their oxidizing activity, NO_x have also an important action as catalyzing agents by increasing the rate of the sulphation process [1]. Sulphur dioxide (SO_2) attacks calcite ($CaCO_3$) of calcareous stone and after reaction produces gypsum ($CaSO_4.2H_2O$). Gypsum forms black crusts at rain sheltered areas and accelerates erosion at areas not exposed to the rain's action [1]. The most frequently encountered chemical constituents in black crusts are gypsum, calcite, silicates, potassium nitrate and numerous organic constituents in lower concentrations [2] [3].

Black crusts greatly affect the aesthetic view of the historical monuments. Their thickness ranges from 200μm to several mm. Previous studies evidenced that black crusts can be distinguished, according to their chemical composition, into sub-layers [2]. Discontinuities detected in the crusts function as areas, where the deteriorative factors are concentrated. The formation of black crusts on marble surfaces is associated with a discoloration of the surface and the development of a coating with colour ranging from orange-brown to brown-black depending on the exposure and the chemical composition of the stone. Black crusts on the stonework do not resemble homogeneous varnished layers. In contrast, by observing the crusts under a monitoring system that gives information about the texture, such as a Fiber Optic Microscope Monitoring system (FOM), it becomes evident that small black particles, in a small distance between them are located within the matrix of encrustation. These black particles are responsible for the coloration of the crust.

Figure 1 depicts a marble surface covered with black crusts as observed under the FOM system.

Figure 1: A stone surface containing black and white particles under the Fiber Optic Microscope.

The presence of deteriorated areas on marble surfaces not only alters the visual appearance of the stonework, but also leads to further decay. Gypsum layers and black crusts absorb a great amount of humidity resulting in the development of a lamellar texture and subsequently to the abruption of the crust and loss of the stone material. Furthermore, particulate matter accumulated in black crusts accelerates the erosion rate by its catalytic action. Therefore, the employment of chemical cleaning becomes essential not only for the conservation of the deteriorated areas, but also for preventing further erosion phenomena. In order to select the most appropriate cleaning methods, the key step is an effective diagnosis process. More specifically, the type of the deterioration patterns, as well as the extent and the thickness of the eroded areas should be defined.

The diagnostic processes used so far for quantifying the deterioration effects are mainly based on the removal of samples from the monument and subsequent chemical analysis. Thus, all these methods are considered destructive. The development of non-destructive methods that could be applied in situ is an aspect under investigation.

Previous work evidenced that the use of computational methods with the aim of quantifying the decay effects in works of art is quite difficult. Lebrun [3] developed a system with the aim of quantifying the colour alteration due to weathering. In the aspect of old paintings restoration by using Image Processing techniques, M. Pappas and I. Pittas [4] introduced several image processing techniques with the aim of diagnosing the deterioration effects and performing a digital restoration. Furthermore, several image processing techniques were developed in order to extract features of stonework and in particular from marble surfaces [5].

In this study, the non-destructive FOM system, capable of obtaining images from the stone surfaces before and after the chemical cleaning, is employed. Given that the FOM images qualitatively depict the extent of decay, a necessity arose for a quantitative estimation of decay patterns. This can be achieved by applying special algorithms to the studied images with the aim of discriminating locations, where deteriorated areas prevail. Decay patterns, such as black and white particles differed in their chemical composition, were discriminated after the algorithm study, accordingly. The algorithm study provides information on the shape, surface size and thickness of the decay patterns.

2 Experimental Setup

The algorithm reported in this paper was tested in a set of images taken by a FOM system. The images represent two broad categories according to the conditions of exposure. More specifically, these images are related to surfaces of the monument which are unsheltered or sheltered from the rain action. The deterioration effects are greatly associated with the exposure to rain's and wind's action, as well as the climate conditions in general. Sheltered surfaces develop crusts more extensive in size, thicker and darker in colour. On the other hand, stone surfaces more exposed to the climate conditions demonstrate different degradation phenomena, such as thinner crust layers, discoloration and variety of the crust colour.

The studied surfaces were located on columns from the National Archaeological Museum of Athens, Greece. The FOM images were taken from reedings and flutings of columns. Flutings function as cavities in which pollutants and airborne particles (fly ash, metal oxides, dust grains etc) are deposited, while in reedings fewer pollutants are accumulated because of the washing effect of the rain.

The type and the extent of pollutants encountered on reedings and flutings of columns were also verified by chemical investigations. The chemical study was also performed on the cleaned surface in order to assess the cleaning efficiency. The chemical methods employed for the removal of the pollutants from the stone surfaces, are the application of: (a) a poultice with biological and chemical agents (BP), (b) an anionic resin in combination with ammonium carbonate (DS) and (c) a wet micro-blasting (WMB).

BP is a cleaning method employed a poultice of carboxymethylcellulose which contained disodium salt of ethylenediaminetetraacetic acid (EDTA), ammonium and sodium bicarbonate and de-ionized water, capable of removing heavy layers of sulphate, carbon particles and biological deposits. Different durations of application were conducted according to the thickness of the black crust and the pollutants to be removed. DS cleaning method corresponds to a process that uses anionic resin in combination with ammonium carbonate. This procedure is applied multiple times by changing each time the duration of the application, depending on the type and the amount of the pollutants to be effectively removed. It was experimentally pointed out that specimens originating from sheltered surfaces were efficiently cleaned after a DS application of 40 minutes duration. Finally the third chemical cleaning method (WMB), used a wet micro blasting machine (Gagemark Ltd) with micro-particles of alumina (with diameter <60 μm) and de-ionized water. The mechanical action of the alumina micro-spheres results in the removal of the black encrustation.

3 Algorithmic Approach

In order to assess in a quantitative way the efficiency and the accuracy of several chemical cleaning methods in removing the black crusts, FOM images before and after any chemical intervention are being processed in gray-scale mode.

The deterioration patterns as both observed in FOM images and detected in chemical analyses are distinguished into two main categories: "black particles" and "white particles". "Black particles" are associated with the presence of alumino-silicates, carbonate particles, metal oxides and other pollutants entrapped in the gypsum cavities. On the other hand, "white particles" represent deterioration patterns associated with gypsum crystals and re-crystallized $CaCO_3$.

The degree of corrosion and the efficiency of the employed chemical cleaning methods were evaluated by considering the number of the black and white particles, as well as their percentage of the marble's surface coverage. In the detection process the shape preservation of black and white particles plays an important role.

Besides the limitations characterized any detection process, a good spot detector should have some basic properties, as far as insensitivity to large-scale intensity variations is concerned. These large-scale intensity variations are characterized by low spatial frequencies. Moreover, the detection process should be adaptive to the noise level within a neighbourhood. Spots with high contrast can be detected even within an area of a high noise level. Therefore, the detector should be adapted to a size which approximates the size of the deterioration patterns.

3.1 Detection Process

The detection process consists of the combination of morphological filtering and a difference of Gaussians spot detector ([6], [7]). The Gaussian detector can exactly detect the location of the deterioration patterns without being able of preserving their shape. In contrast, the morphological filter preserves the shape of deterioration patterns, but gives a higher false positive rate. The combination of the results of the two filters guarantees both preserved shape and a low false positive rate.

3.1.1 Weighted difference of Gaussians

The Gaussian Detector consists of several steps. At first the original image f(x, y) is low-pass filtered using a Gaussian kernel with standard deviation σ equal to 4 pixels.

$$f_1(x,y) = f(x,y) - G_4[f(x,y)] \quad (1)$$

The difference of Gaussian Filtering consists of the subtraction of one smoothed version of an image from another having a different degree of smoothing. Two Gaussian kernels with different standard deviations are used to smooth the image. The standard deviations of the Gaussian kernels are chosen to reflect the dimensions of black and white particles and the inter-particle distance. The weighted version of Gaussian method is used assigning a weight of 0.8 to the kernel of larger width for the detection of black spots, while the inverse process is followed for the detection of white particles. This procedure is applied to the subtracted image f1. Therefore, the two equations used for the detection of black and white particles, respectively, are addressed by the following relationships:

For black particles detection,

$$f_2 = 0.8 \times G_6[f_1(x,y)] - G_{0.25}[f_1(x,y)] \quad (2)$$

and for white particles detection,

$$f_2'(x,y) = 0.8 \times G_{0.25}[f_1(x,y)] - G_6[f_1(x,y)] \quad (3)$$

The image resulting from the Gaussian filters $f_2(x, y)$ is processed by following the procedure described below. At first, the histogram of the image $f_2(x, y)$ is extracted and the standard deviation is computed. At a further step, a first threshold equal to k1 times the standard deviation is applied. The standard deviation is recalculated, by using only the pixels that are beyond the initial threshold. The final threshold was set as k_2 times the recalculated standard deviation. The process followed for the determination of white particles is quite similar. The standard deviation is re-calculated through considering beyond the threshold value k_1*std_1, k_1 and k_2 are selected to minimize the false positive and negative rate. According to previous studies ([7], [8]), k_1 and k_2 should belong in the range [1,3] given that standard deviation is greater than 1.

3.1.2 Preserving the Shape of the Spots

As it was previously discussed, the Gaussian Filtering procedure is very reliable in detecting spots ; nevertheless, the shape of the spots is distorted: the boundary of the individual spots is smoothed. For further analysis, however, the original shape should be preserved, in particular when the spots have bizarre boundary. This is achieved by applying a morphological filter operation to the image under consideration. The theoretical background of the morphological operations is well known in the Machine Vision community.

At first the top-hat transform is used to enhance white particles that have size smaller than the structuring element. The structuring element M is defined as a circle of 13 pixels of diameter. Similarly, in order to detect the white particles the bot-hat transform is used. In the case of the white particles detection, the structuring element is also a circle of the same diameter. At a further step, the histogram of the resulted image (which came out after the bot-hat and the top-hat transforms) was extracted and the standard deviation was calculated. For the detection of black spots, after the calculation of the standard deviation of the image resulted from the bot hat transform, an initial threshold equal to k1 times the standard deviation std1 is applied. The standard deviation is recalculated by considering only the pixels that are beyond the initial threshold. Finally, a threshold equal to k_2 times the recalculated standard deviation is applied. All the pixels with values greater than the threshold value are considered to compose the black particles. The procedure used to determine the white particles is quite similar, but in this case, the image studied is the result of the top-hat transform. In both cases, in order to eliminate the noise and other sharp details the images obtained after the thresholding are morphologically filtered. The selection of the structuring element is dependent on the size and shape of the deterioration patterns.

3.1.3 Reconstruction by Conditional Thickening

The shape of the spots determined by the morphological method is better preserved than the detection by the Gaussian detector, as far as false positive locations of spots and merged regions are concerned. The Gaussian detector determined the spots and their topology. In order to reconstruct the shape of the spots optimally, both methods are combined. The idea was to exploit the strength of both concepts, by detecting the spots with the Gaussian detector and expanding them, but not allowing their merge or grow beyond the size given by the result of the morphological filter operation. For this purpose, a morphological conditional thickening is applied. The operator $\otimes$ of X relative to Y with the pair of structuring elements (M_1, M_2) is defined as follows:

$$(\mathrm{M}_1,\mathrm{M}_2)\otimes X\mathrm{Y} = \mathrm{Y} \cap \left(X \cup \left((\mathrm{M}_1 \Theta X) \cap \left(M_2 \Theta X^c\right)\right)\right) \tag{10}$$

For the segmentation of the black and white particles, the structuring element M has the following structures:

$$\mathrm{M}_{1,1} = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \mathrm{M}_{1,2} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix} \quad \mathrm{M}_{2,1} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad \mathrm{M}_{2,2} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix}$$

and every rotation of these matrices around 90^o.

The result of the conditional thickening of X onto Y with the structuring element M is the conjunction of the partial results of the equation above reported for every pair (Mi1, Mi2).

$$\mathrm{E} = \bigcup_{i=1\cdots 8} \mathrm{M}_i \otimes XY \tag{11}$$

The equation is applied for E=X until E does not change any more. The special property of M is that either X increases until the boundaries of Y are reached, or two subsets of X are separated through a line of one pixel in width. Consequently, E is always a subset of Y and contains as many objects as the intersection of X and Y. A conjunction of two objects of X is prevented by the structuring element M, because it extends X only with pixels of Y not disturbing the topology of X. This means that spots detected by the Gaussian detector are both extended by topologically unimportant pixels and the results are always intersected with the corresponding ones of the morphological method. In (11), X represents the result of the detection process and Y represents the result of the reconstruction one giving the shape of the spots. The intersection in each step assumes that after the conditional thickening, the remaining spots are present in both X and Y. Therefore, the intersection step determines the place and the number of the black\white particles, Y determines the shape, while the structuring element M prevents the confluence of several spots.

4 Results

Through figures 2 and 3 we provide visual evaluation of the results derived by the Conditional Thickening algorithm tested in various surfaces. Furthermore, statistical data extracted from the image processing can quantify the deterioration state. Figure 2 depicts a black crust located on an untreated fluting located at sheltered areas (a), while (b) and (c) illustrate the black and white particles, respectively, as detected by Conditional Thickening Algorithm.

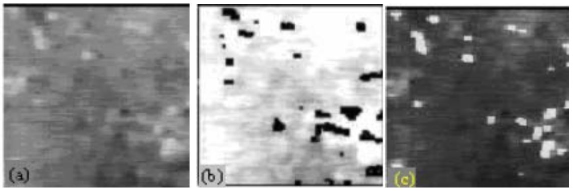

Figure 2: (a) Sub-area of a black crust located on a fluting at sheltered areas, (b) Black particles detected by the Conditional Thickening Algorithm superimposed on (a) and, (c) White particles superimposed on (a).

Figure 3 reveals the algorithms efficiency in detecting black particles. Even the extent of black particles and their sporadic presence resembles to the size and spatial distribution determined by prior chemical studies [2] [8]. To estimate the alterations (in the spatial density and extent of decay areas) we also provide visual results depicting the corrosion state after cleaning. Thus, figure 4 illustrates sheltered fluting surface cleaned by the DS method.

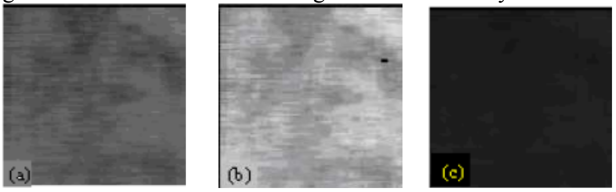

Figure 3: (a) Sub-region of an image illustrating a fluting located at sheltered areas cleaned DS, (b) black particles detected by the Conditional Thickening Algorithm superimposed on (a) and, (c) detected white particles superimposed on (a).

Figures 3(a) through (c) illustrate that the applied algorithm revealed less deterioration patterns after the application of the chemical cleaning. This observation is also verified in the statistical data obtained after the application of the Conditional Thickening Algorithm of the marble surfaces. In the statistical elaboration different conditions of exposure of black crusts were considered. In particular, rain-washed and sheltered areas, as well as areas with intensive (fluting) and moderate accumulation of atmospheric deposits (reeding) were studied.

Figures 4, 5 and 6 show the results of the statistical processing of the surfaces studied by the Conditional Thickening Algorithm. In particular, Figure 4 depicts the number of black particles detected on surfaces with different exposure to the rain action. Figure 6 pointed out that after the application of the chemical cleaning methods the percentage of the surface covered by black particles is significantly reduced.

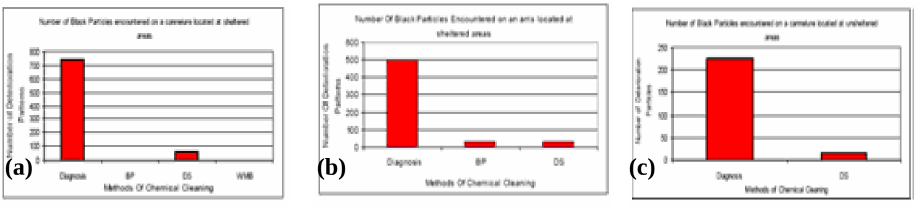

Figure 4: (a) Number of black particles detected on sheltered flutings for both prior and after cleaning, **(b)** similar to (a) regarding sheltered reedings, **(c)** similar to (a) and (b) for unsheltered flutings.

At this point it is worth comparing the deterioration pattern sizes encountered on areas of the monument with different exposure conditions. In Table 1 the differences in the distribution of the surface sizes, obtained from the statistical processing of the results, are reported. The studied samples are flutings and reeding both located at sheltered areas before the chemical cleaning.

Table 1

	Lower-Quartile	Upper-Quartile	Median
Fluting (Sheltered)	10	25	16
Reeding (Sheltered)	8	21	13

The results reported in Table 1 indicate that the distribution of black particles sizes encountered on flutings is spread to greater values than the distribution of black particles sizes detected on reedings. The above observation is quite reasonable by considering that flutings function as areas of pollutant accumulation, while reedings represent more washed-out areas.

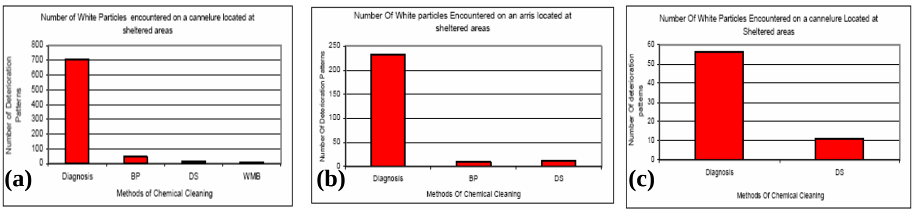

Figure 5: (a)**:** Number of white particles detected on sheltered flutings (both prior and after cleaning), (b) same as (a) for sheltered reedings, (c) same as (a) and (b) regarding unsheltered flutings.

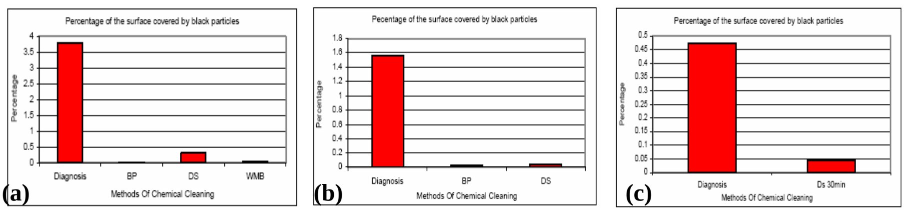

Figure 6: (a) Mean *Percentage of sheltered flutings surface covered by black spots (both prior and after cleaning), (b) similar to (a) regarding a sheltered reeding, (c) similar to (a) and (b) for an unsheltered fluting.*

In this study, the thickness of the black crusts was approached in a rather qualitative way. In particular, the distribution of the gray levels in the areas determined as “black” or “white” particles was evaluated. It was observed that on the images depicting surfaces with crusts of greater thickness, the applied approach evaluated distributions of gray levels that are spread to lower values. This result evidences that a straightforward relationship occurs between the thickness of the crusts and the distribution of gray levels. It was verified that the black crusts are diminished after the chemical cleaning; the intensity of the remaining particles is increased, since they have been appeared brighter and less disturbing in a macro-scopical point of view. This result is quite expectable since it indicates that even crusts, which have not been removed after the cleaning process, were eliminated in thickness.

In Table 2 the alteration of the gray levels distribution before and after the chemical cleaning is shown. The studied surfaces are flutings located at sheltered areas.

Table 2

	Lower-Quartile	Mean Intensity	Upper-Quartile
Diagnosis	49	57.89	73
DS	67	75.74	84
BP	61	68.2	77
WMB	62	73.21	96

Table 2 shows that the distribution of gray levels within black particles is shifted to higher values due to cleaning. The data presented in Table 3 indicate that on the black crusts located on a sheltered fluting, the distribution of gray levels is spread to lower values. This observation means that in the sheltered fluting the black crusts are darker in color. This assessment is expectable and is in accordance with the results obtained by the chemical analyses.

Table 3

	Lower-Quartile	Mean Intensity	Upper-Quartile
Fluting-Sheltered	49	57.89	73
Reeding-Sheltered	85	95.97	107
Fluting-Unsheltered	90	96.31	104

5 Conclusions

The paper tackles with the problem of developing machine vision approach to detect corroded areas on stone surfaces. In the current work the systems performance was tested on a large set of images obtained through a Fiber Optics Microscope. The basic contribution of this work is that it uses a non-destructive computer aided approach in order to provide quantitative results on based on the structural components of black crusts. The basic principle for the development of the computer vision approach is to determine he exact location of corroded areas while preserving their extent and shape.

The detected deterioration patterns are classified into two broad categories defined by the terms “black particles” and “white particles”. This discrimination was performed according to the chemical composition of the deterioration patterns. Alterations on the size and the spatial density of the detected black/white particles (before and after the chemical cleaning) were also studied. The results revealed that the sizes and the number (per surface unit) of the deterioration areas are affected (eliminated) due to cleaning condition. The spatial density of corroded areas was also considered for estimating the efficiency of cleaning techniques.

References

[1] D. Cammufo, *“Acidification and its Policy Implications”,* T.S Schneider (Ed.), Elsevier-Amsterdam, 1986.

[2] P. Maravelaki-Kalaitzaki, G. Biscottin, “Origin, characteristics and morphology of weathering crusts on Istria stone in Venice”, Int. J. of *Atmospheric Environment, Vol. 33, No. 11,* 1999, pp. 1699-1709.

[3] V. Lebrun, E. Bonino, J.F Nivart, E. Pirard, ”Development of specific acquisition techniques for field imaging-Applications to outcrops and marbles”, *Geovision, Int. Symp. On imaging applications in Geology*, (1999), pp 165-168.

[4] M. Pappas, I. Pitas, “Old painting digital color restoration”, *Noblesse Workshop On Non-Linear Model Based Image Analysis,* (1998) Glasgow, Scotland.

[5] C. Boukouvalas, J. Kittler, R. Marik, M. Petrou, “Automatic grading of ceramic tiles using machine vision”, In *Proc*. IEEE International Symposium on Industrial Electronics, 1994, pp. 13–18.

[6] M.F Salfity, G. H. Kaufmann, P. Grannito, H. A. Ceccato, “A Computer-Aided Diagnosis for Automated Detection and classification of clustered microcalcifications in mammograms”, *3^er^. Simposio Argentino de Informática en Salud.* 2000, pp. 41-47.

[7] J. Dengler, S. Behrens, J. F. Desaga, “Segmentation of Micro-calcifications in Mammograms”, *IEEE Transactions on Medical Imaging, Vol. 12,* 1993, pp. 634-642.

[8] P. Kapsalas, M. Zervakis, P. Maravelaki-Kalaitzaki, "Evaluation of image segmentation approaches for non-destructive detection and quantification of corrosion damage on stonework", Int. J. of Corr. Science, Vol. 49, No. 12, 2007, pp. *4415-4442***.**