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SPECKLE CORRELATION METHOD FOR MONITORING OF LOCALIZED CORROSION IN WATER ENVIRONMENT

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A new correlation-based method for evaluation of the degree of localized corrosion damage on rough surface using video inspection data signal is proposed. The possibility to evaluate very low values of corrosion degree in the presence of high-level noises, typical of water/underwater inspection of constructions is a key advantage of the proposed method. Results of the correlation measurement system calibration and evaluation of its accuracy are presented. Parameters of signal models are obtained from laboratory experiments for pitting corrosion testing of steel samples.

Keywords: *localized corrosion degree, correlation coefficient measurement, speckle signal*

СПЕКЛ-КОРЕЛЯЦІЙНИЙ МЕТОД ДЛЯ МОНІТОРИНГУ ЛОКАЛЬНОЇ КОРОЗІЇ У ВОДНОМУ СЕРЕДОВИЩІ

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Запропоновано новий кореляційний метод оцінювання ступеня пошкодження локальною корозією шорсткої поверхні з використанням сигналів відеоінспекції. Як інформаційний параметр запропоновано використати нормований коефіцієнт кореляції між спекл-сигналами (зображеннями спекл-сигналів) світла, розсіяного мікронерівностями досліджуваної поверхні. Виконано нормування залежності коефіцієнта кореляції від ступеня пошкодження досліджуваної поверхні локальною корозією. Ключовою перевагою запропонованого методу є можливість оцінювати малі ступені локального корозійного пошкодження поверхні досліджуваного матеріалу за значних шумів, що є типовим для інспекції поверхонь конструкцій у водному середовищі. Подано результати калібрування і оцінки точності вимірювальної системи, у тому числі випадкову та сталу складові (зміщення) похибки визначення коефіцієнта кореляції та ступеня корозійного пошкодження. Показано, що запропонований метод роботоздатний за використання апаратного забезпечення середнього рівня складності (розширення системи порядку 1000×1000 пікселів) і забезпечує надійне визначення ступеня локального корозійного пошкодження у діапазоні 0…60% з наростанням середньоквадратичного відхилення сигналу вхідного шуму до 38 градацій шкали сірого за робочого діапазону вимірювальної системи у 256 градацій. Використання знімальних систем з більшим розширенням дасть змогу зменшити похибку визначення ступеня пошкодження завдяки вибору області чи областей оцінювання шуму з більшою кількістю пікселів. Параметри моделей сигналів отримані зі стандартних лабораторних випробувань трьох типів сталей з різною опірністю до пітингової корозії.

Ключові слова: *ступінь пошкодження локальною корозією, вимірювання коефіцієнта кореляції, спекл-сигнал.*

Introduction. Evaluation of the localized corrosion degree is of practical importance in monitoring the corrosion damage of metal surfaces in seawater. Visual (or video) inspection with involvement of optical images and digital image processing is widely used for evaluation of the degree of localized corrosion. It is based on the detection of contours (boundaries) of the damaged regions and calculation of their area relative to the whole inspected surface. However, the evaluation of the low values of corrosion degree and/or evaluation of the surfaces with small size damages are essentially complicated, first of all because of the inaccuracy of contours detection that has essential impact on calculation of the damage area in the case of small size damages. For example, in the case of the circle damage with a diameter of 10 pixels on digital image, even minimal inaccuracy of contour detection – 1 pixel will result in 40% error in calculation of its area. Besides, the contour detection inaccuracy (and damaged area evaluation inaccuracy) essentially increases when the inspected surface has the roughness (R_z parameter) above 1 μm, what is typical of ordinary metal surfaces in constructions. This takes place because the optical light signal, reflected from such, has an essential noise component, caused be multiple diffusion of light on the surface relief roughness [1]. Optical signal, reflected from the inspected surface is also diffusing in environment – on small particles of corrosion products and metal particles in seawater and on the optical survey system window. So, the optical signal in a video inspection system has an essential random noise component as a result of multiple light diffusion on small particles. On the other hand, nucleation, appearance and development of localized corrosion damage on the rough surface is a result of the random process, related to many random parameters, like local surface relief, local concentration of aggressive corrosive environment, potential, current density, etc. [2–5]. It finally results in local damage initiation and development.

So, it is necessary to analyze the mostly random process of corrosion damage initiation and development, using the optical signal with the essential random noise component. Naturally, the analysis will be performed using parameters of random processes in these correlation coefficients. Sensitivity of the correlation coefficient of optical signals from the metal surface to the process of corrosion is shown in [6–10]. Unfortunately, no correlation – based methods for assessment of the degree of localized corrosion damage of the surface, its calibration, accuracy evaluation, are proposed. This diminishes the advantage of the correlation method, despite of its high sensitivity.

Basic assumptions and selection of the parameters for simulation. Let us assume that the optical signal, reflected from the tested surface and passed through the water environment, is a result of multiple light scattering. For calibration of correlation-based video inspection system, we will use the model of multiple scattered light signals, known as a speckle-signal described in [11]. As a model for localized corrosion we will use pitting corrosion. Pitting corrosion is typically localized corrosion. Pit nucleuses appear chaotically, uniformly distributing on the rough surface. Then they can repassivate and die or develop further in the form close to a circle, achieving the metastable and sable growth stages [2–5]. It is established, that pits on the metal surfaces pass from the metastable stage to the stable growth stage for the diameter range of 10…100 μm [2–5]. They can increase in a diameter, join with neighboring ones, but can also be stable in the visible diameter on the surface, developing undersurface and in depth of the material. Image of the speckle signal, reflected from the rough surface, was simulated by means of series of operations, shown in Fig. 1. Image resolution was set close to that of the ordinary video system standard –750×750 pixels. All calculations for this paper were also performed using Harris ENVI software. Width of autocorrelation function of the signal was increased 10 times (to 10 pixels) by means of Fourier-transform based low-pass filtration. This corresponds to the above mentioned range of pit diameters (10:1) in transition to the stage of stable growth and development. Signal range was scaled (with some “gaps” on top and bottom) within 256 gray scale, that matched standard 8-bit video signal. Corrosion damage and noises were introduced into the model of speckle signal as explained in Fig. 2. Corrosion damages were established as sets of 52 uniformly distributed circles of uniform brightness, removing random speckle signal. It is close by form and nature of distribution of pitting damages, visible on the surface [2–5]. Signal value in the simulated corrosion damage areas was set at the level of 60 gray scale, that corresponded to the average value obtained during specially provided testing for pitting corrosion of the rough metal samples in the environment simplified model of sea water in the lab. Increase in the degree of corrosion damage was simulated by increasing the diameters of circles. Table 1 presents the values of the degree of corrosion damage of the sample surface, used for simulations.

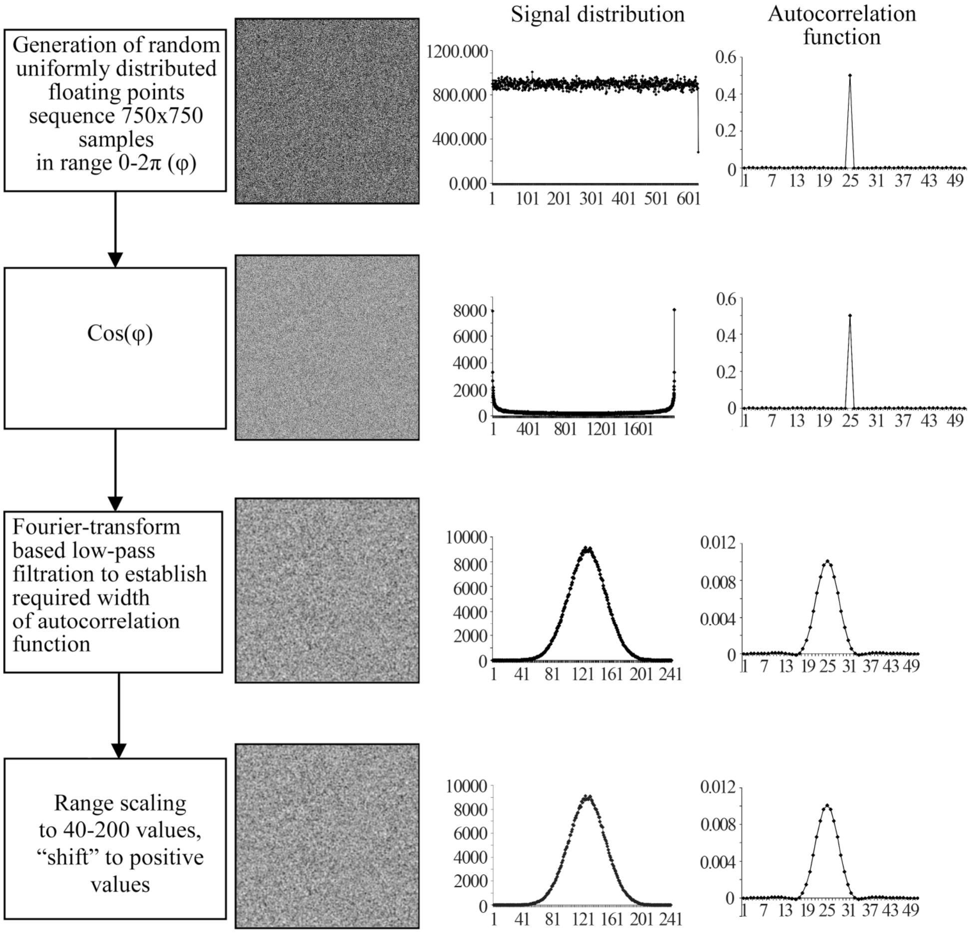

Fig. 1. Algorithm for simulation of speckle signal from the specimen surface.

Table 1. Values of the degree of localized corrosion damage used for calibration

Image #	1	2	3	4	5	6	7	8	9	10	11	12	13
Corrosion degree, %	0	0.35	0.78	1.18	1.64	2.12	2.77	3.43	4.24	5.11	5.98	7.03	8.08
Image #	14	15	16	17	18	19	20	21	22	23	24	25	26
Corrosion degree, %	9.28	13.24	16.24	20.41	25.20	30.28	35.99	39.81	46.13	53.11	60.47	71.75	83.02

Besides, it is necessary to introduce in the above simulated image of the speckle signal the additional random noise. This noise will simulate the random diffusion of the signal on small size particles (on the surface, in the environment, on optical windows), electronic noise, etc., that are not related to local corrosion. The value of the real video signal in the specimen surface image that is decreasing and fluctuating during corrosion in seawater is established from the results of preliminary laboratory testing. Distribution of such noise/fluctuations obtained in time lag 1000 s, evaluated with Q–Q plot (Fig. 3), is explained by well enough matching with normal distribution. Experimentally obtained time dependence of the RMS (root mean square) noise in a frame of 50 $\times$50 pixels without visible localized corrosion damage is presented in Fig. 4. Noise was introduced into the model of speckle signal by means of subtracting specially generated random signals from a speckle signal with introduced corrosion damage. These signals were generated by ENVI random program as sets of normal distributed sequences of size 750×750 of random numbers with some RMS values and zero mean. The RMS of noise signals established for simulation are explained in Table 2. Seed number for each series was also set into a random number to provide independent noise sequences for simulations.

Table 2. Values of RMS of random sequences used for noise simulations in video signal

RMS, gray scale levels	3.1	6.1	9.9	12.8	16.9	19.1	22.7	25.5	29.5	32.0	35.0	38.0

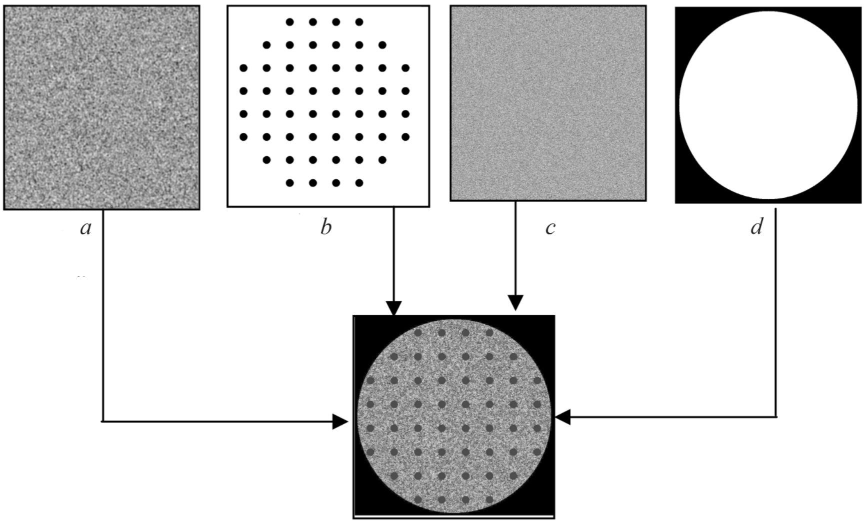

Fig. 2. Algorithm for introducing corrosion, noise and working area in the signal model: *a* – model image of a speckle signal; *b* – corrosion damage of a model image; *c* – random noise image; *d* – mask.

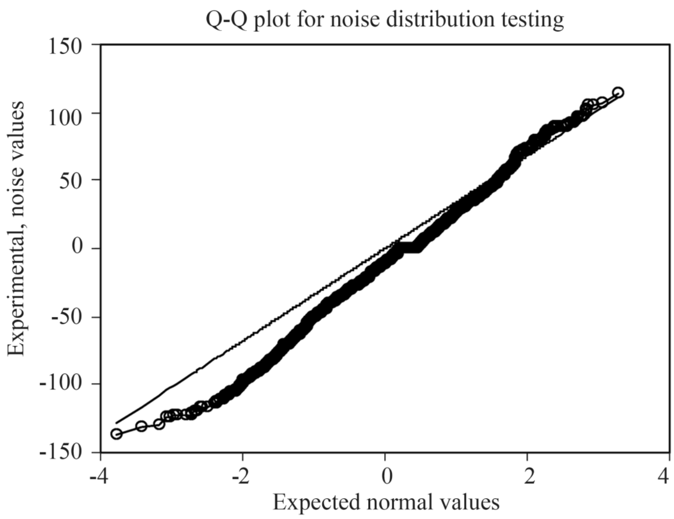

Fig. 3. Q-Q plot of normal and experimental noise distributions in the frame of 50 ×50 pixels.

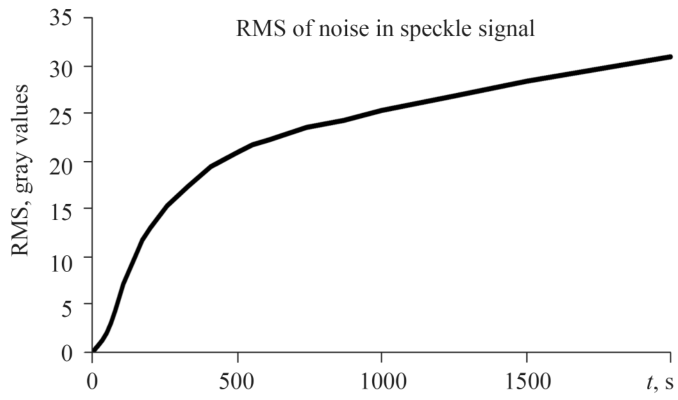

Fig. 4. Dependence of RMS of noise in speckle signal on time.

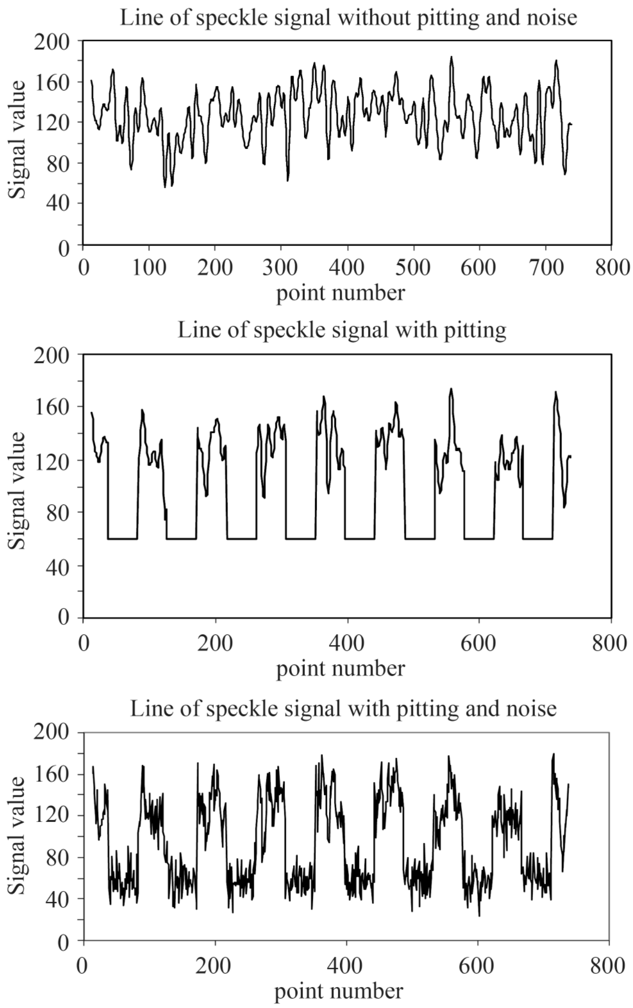

Fig. 5. Changes in the signal line during introduction of corrosion damage and noise.

Signal in the speckle image was also masked by a circle of a diameter 740 pixels to correspond to the typical form of the specimen surface during accelerated laboratory testing in the seawater model. An example of a simulated line of the speckle signal without corrosion damage, with damage and with damage and noise is explained in Fig. 5.

Method for correlation-based data processing. The influence of corrosion and noise on a speckle signal, diffused by the sample surface results in decorrelation (decrease of correlation coefficient) between signals collected in different time moments. Calibration of the speckle correlation measurement system is reduced to establishing the dependence of correlation coefficient between speckle images, obtained at different time moments ρ, and the increase of the degree of localized corrosion damage of ΔC surface for this time interval. For such calibration the Pearson correlation coefficients between the simulated speckle image without corrosion and a set of simulated speckle images with introduced corrosion data (without introduced noise) were calculated. The obtained calibration dependence of measurement system $\rho(\Delta C)$ is explained in Fig. 6.

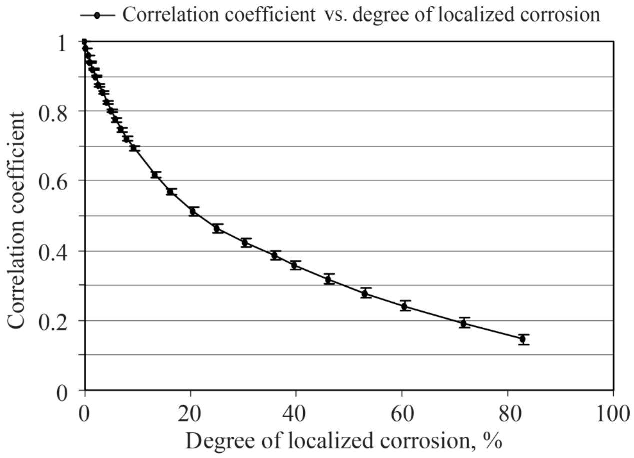

Fig. 6. Dependence of Pearson correlation coefficient on the degree of localized corrosion without noise.

In the case of the additional noise absence, the accuracy of such measurement system will be limited by the sample size (430 000 samples), used for estimation of the correlation coefficient. The RMS of the error random part for estimation of the Pearson correlation coefficient was evaluated using the interval between confidence limits as explained in [12]. In accordance to [12], the confidence interval for the expected value $\hat{\rho}$ of the Pearson correlation coefficient obtained for the sample size n can be evaluated as follows:

$$\hat{\rho}^* \pm z_{a/2}\sqrt{1/(n-3)}\,, \tag{1}$$

where $\hat{\rho}^* = \ln\left[\frac{1+\hat{\rho}}{1-\hat{\rho}}\right]\Big/2$ is the Fisher transformation of $\hat{\rho}$; $z_{a/2} = 2{,}576$ for confidence interval 99%; n is the sample size.

Establish the upper and lower limits for the Fisher-transformed correlation coefficient as:

$$\rho^*_{up} = \hat{\rho}^* + z_{a/2}\sqrt{1/(n-3)}\,, \tag{2}$$

$$\rho^*_{low} = \hat{\rho}^* - z_{a/2}\sqrt{1/(n-3)}\,. \tag{3}$$

The upper and lower limits for the interval of evaluation for expected value of the Pearson correlation coefficient were obtained:

$$\hat{\rho}_{up} = (\exp(2\cdot\rho^*_{up}) - 1)/(\exp(2\cdot\rho^*_{up}) + 1)\,, \tag{4}$$

$$\hat{\rho}_{low} = (\exp(2\cdot\rho^*_{low}) - 1)/(\exp(2\cdot\rho^*_{low}) + 1)\,. \tag{5}$$

Assuming that the confidence interval for the correlation coefficient is equal to $6 \cdot \sigma$ obtain the RMS of its random error:

$$RMS_{\rho} = (\hat{\rho}_{up} - \hat{\rho}_{low}) / 6 . \tag{6}$$

Dependences of the RMS of the random error of the correlation coefficient estimation on the expected value of the correlation coefficient for 430 000 samples and 2500 samples obtained from Eq. (2)–(6) are presented in Fig. 7. The RMS of the random error for the sample size 2500 is also presented in Fig. 6 (as error marks for the correlation coefficient).

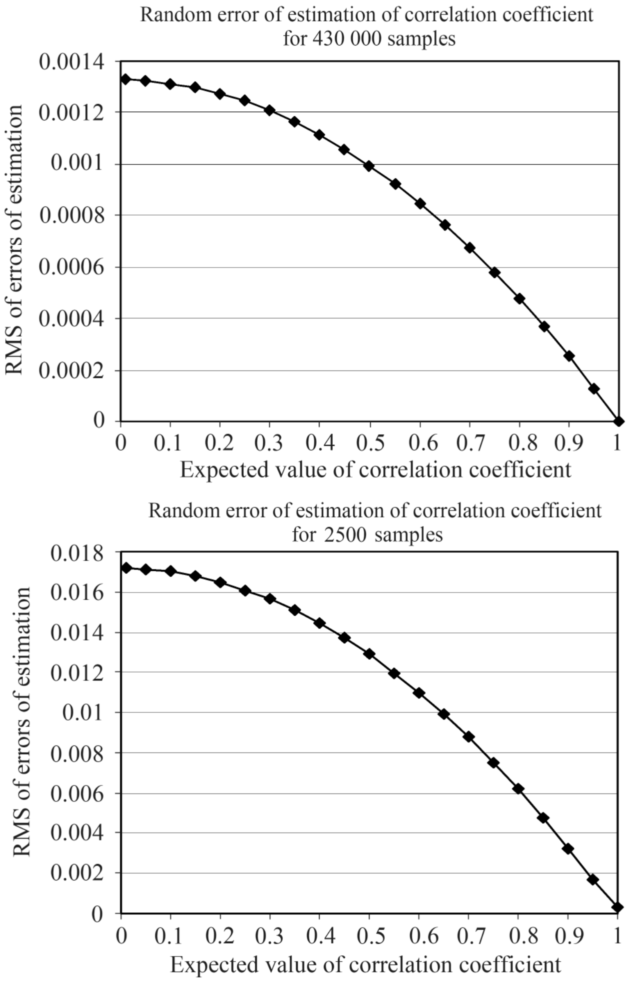

Fig. 7. RMS of random errors for estimation of the Pearson correlation coefficient.

As it was mentioned above, the compensation of the noise influence on the correlation coefficient is an important problem. As we can see from Fig. 4, real noises have essential RMS values that are compatible with RMS of the speckle signal from a video system. So, it provides an essential impact on the correlation coefficient, thus causing additional inaccuracy. Such interference should be estimated and compensated. The attempt to estimate the unknown partial correlation coefficient from the evaluated multiple correlation coefficients is known [13]. As it is known from [13], for the set of three correlated random populations named, for example, 1, 2 and 3 with known multiple correlation coefficients between them – $\rho_{12}, \rho_{13}, \rho_{23}$, a partial correlation between two of them (1 and 2), removing the influence of 3, can be calculated as follows [13]:

$$\rho_{12|3} = \frac{\rho_{12} - \rho_{13} \cdot \rho_{23}}{\sqrt{(1-\rho_{13}^2)\cdot(1-\rho_{23}^2)}}, \tag{7}$$

where $\rho_{12|3}$ is the partial correlation coefficient between populations 1 and 2 without the influence of population 3. Let us consider that random population 1 is a speckle signal from the sample at time moment $t = 0$, 2 is a speckle signal from the sample for current time $t = T$ and 3 is a noise at current time moment $t = T$. Then, the known estimations of multiple correlation coefficients allow us to remove the influence of noise and to evaluate the localized corrosion degree – with $\rho_{12|3}$ and calibrating dependence (Fig. 6). The essence of the problem consists in the evaluation of the multiple correlation coefficients of noise, which is not related to the localized corrosion impact on a speckle signal. For the evaluation of the correlation parameters of noise, the author proposes to select some area on a speckle image of the sample without visible corrosion damage and to estimate such parameters inside such an area. Sample size of 2500 pixels can be suitable to the mentioned video system – on the specimen image in a frame of a circle with a diameter of 740 pixels it is easy to find at least one area of $\sim 50\times 50$ pixels without corrosion damage.

The RMS of random error for estimation of the correlation coefficient for such a sample size with Eq. (2)–(6) is explained in Fig. 7. As it is seen from Fig. 7, the RMS of the error for noise estimation area (2500 samples) is bigger in about one order for the whole working area (430 000 samples), but it is still low enough (≤ 0.02) even at very low correlation coefficient values (about 0.1…0.3) and is small enough for the localized corrosion measurements (Fig. 6).

Let the selected area for noise evaluation with coordinates on the speckle image $(x_{\min}, x_{\min+50}), (y_{\min}, y_{\min+50})$ be called *AN*. A noise signal will be defined as the difference between a speckle signal at time moment $t = 0$ and current time moment $t = T$:

$$N_{t=T}(i, j) = AN_{t=0}(i, j) - AN_{t=T}(i, j), \tag{8}$$

where *i*, *j* are pixel coordinates in the frame *AN*.

The correlation coefficient between a noise and a speckle signal in time $t = 0$ is evaluated as:

$$\hat{\rho}_{13}(T) = \mathrm{corr}(N_{t=T}, AN_{t=0}). \tag{9}$$

Dependence of the RMS of the error random component for such estimation on the correlation coefficient value is explained in Fig. 7.

Now it is necessary to obtain multiple correlation coefficient $\hat{\rho}_{23}$ between a noise and a speckle signal at time moment $t = T$ (with localized corrosion and noise impact). The problem is that it is impossible to separate the influence of noise from the corrosion impact in the whole speckle image (signal). The square of multiple correlation coefficient $\hat{\rho}_{mult}$ can be estimated as in [14], using ratio of variations of appropriate signals (2 and 3). In our case $N_{t=T}$ is obtained from Eq. (8) and $S_{t=T}$ is a signal of the whole working area on the speckle image:

$$\hat{\rho}_{23}(T) = \hat{\rho}_{mult} = \sqrt{Var(N_{t=T})/Var(S_{t=T})}. \tag{10}$$

Random component of an error for such estimation is somewhat less than the error for estimation of $\hat{\rho}_{13}$ because $Var(S_{t=T})$ is evaluated for much bigger population – 430 000 samples. It should be mentioned, that the use of such an attempt is restricted to the inequality $Var(N_{t=T}) \le Var(S_{t=T})$ which proceeds from condition $0 \le \hat{\rho}_{mult} \le 1$ [13, 14].

Simulation, results and discussion. For real experimental data, the random component of the inaccuracy of evaluation of time dependence of $\rho_{12|3}$ (and degree of localized corrosion) can be estimated using partial derivatives of Eq. (7) and RMS of random error values, explained in Figs. 6 and 7. Here estimation of the accuracy of correlation measurement system was performed using the Monte–Carlo simulation method. Correlation coefficients between the simulated speckle signal without introduced corrosion and the simulated signals with different degree of corrosion (all without added noise) were calculated and saved as "exact" control values. For noise simulation, the groups of different 64 normally distributed random sequences of 430 000 digits with zero average for each RMS value in Table 2 were generated for each speckle image with introduced corrosion damage. For this purpose a separate generator of random digits for generation of a seed value for Random procedure in ENVI was used. These random sequences were used for simulation of random noise in a speckle signal as shown in Figs. 2 and 5. Then the simulated speckle signals with introduced corrosion damage and noise were processed in accordance to Eq. (7)–(10). The average values of multiple correlation coefficients ρ_{12}, corrected correlation coefficients $\rho_{12|3}$, degrees of localized corrosion, their variations and the RMS values for each set of simulated data were calculated. Simulation results (as dependences on RMS of noise, introduced into speckle signal) are shown in Figs. 8–17. In Figs. 8 and 9 the dependences of averages and RMS error values of correlation coefficients on the RMS of introduced noise for the established degrees of localized corrosion (in %): 0; 2.1; 5.1; 9.3; 13.2; 20.4; 30.3; 39.8; 53.1; 60.5 are explained. In Figs. 10 and 11 the dependences of the RMS values of random errors of estimations of correlation coefficients on the RMS of introduced noises for the establishment of localized corrosion degree are explained. In Fig. 12 and 13 the dependences of averages (and RMS error values) of the evaluated degrees of localized corrosion for the established exact values are presented. In Figs. 14 and 15 the dependences of the RMS of the random error component for the evaluated degree of localized corrosion on the RMS of introduced noise for the established levels of corrosion degree are shown. In Figs. 16 and 17 the dependences of the differences between calculated averages of the localized corrosion damage degree and exact established levels (0%; 2.1%; 5.1%; 9.3%; 13.2%; 20.4%; 30.3%; 39.8%; 53.1%; 60.5%) from the RMS of introduced noise are explained. As can be seen from Figs. 8 and 9, the proposed technology of correction of correlation coefficient allows obtaining satisfactory results in a wide range of correlation coefficient values up to the critically low values ($\rho \approx 0.2$). Increase in the variation of noises, introduced into a speckle signal, expectedly results in increase in variations of the corrected correlation coefficient (Figs. 10, 11) and variations of the degree of localized corrosion (Figs. 12, 13). The RMS of random errors for the evaluated raw (non-corrected are marked as "nc" and corrected as "c" in Figs. 8–11) correlation coefficients and appropriate values of the corrosion degree are expectedly less, because data from the 430 000 size samples only are introduced into its calculation. Fields of admission of the corrected correlation coefficients are close to overlapping for the RMS of introduced noise equal to 38 gray scale values. In fact, it is a point where the noise range $38 \cdot 6 = 228$ really overlaps almost the whole range of the measurement system (256 gray scales). The minimal RMS value of the introduced noise, used in this study was 3.1 gray scale value, that is $\sim$6 times more than a standard inaccuracy of the signal value digitizing. It results in the RMS of corrosion degree deviations in the range 0.025…0.35%. It means what the selected range for input speckle signal – 256 gray scale values is enough for such measurements. As can be seen from Figs. 8, 9, 11, 12, 16, 17 the average values of the corrected correlation coefficients and evaluated degree of localized corrosion are stable enough with increase in the noise level in the measurement system. As can be seen from Figs. 14–17 variations in the average values of the evaluated values of corrosion degree are much lower than the RMS of their random errors. This confirms the applicability of the proposed technology.

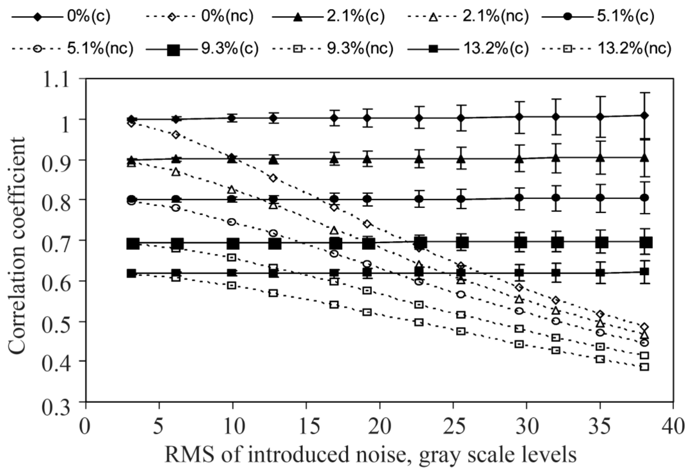

Fig. 8. Dependence of averages of corrected (c) and raw (nc) correlation coefficients on the RMS of introduced noise for localized corrosion damage 0…13%.

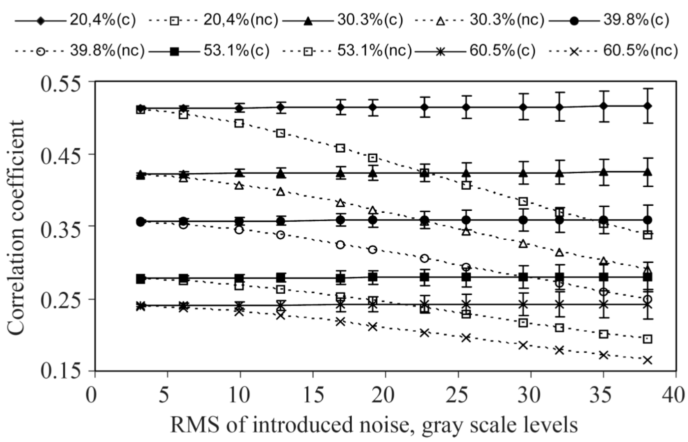

Fig. 9. Dependence of averages of corrected (c) and raw (nc) correlation coefficients on the RMS of introduced noise for localized corrosion damage 20…60%.

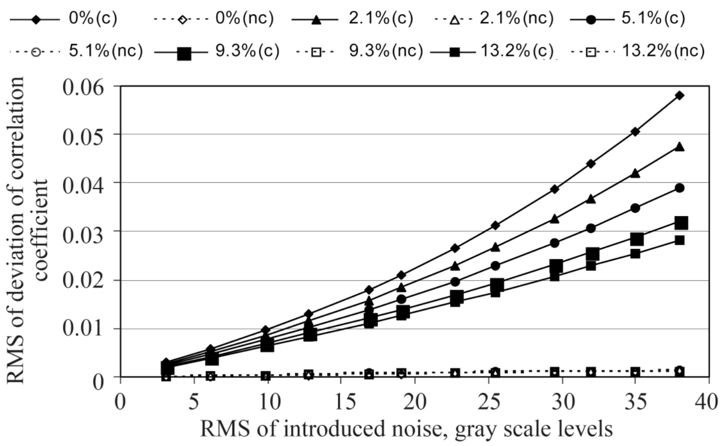

Fig. 10. Dependence of the RMS of random error of corrected (c) and raw (nc) correlation coefficients on the RMS of introduced noise for localized corrosion damage 0…13%.

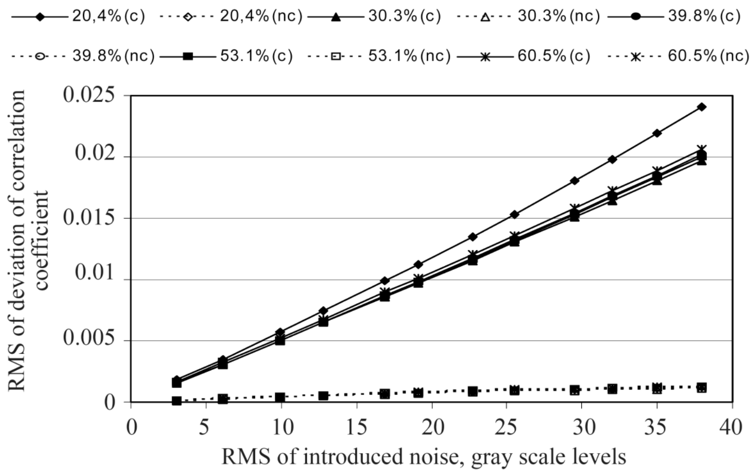

Fig. 11. Dependence of the RMS of random error of corrected (c) and raw (nc) correlation coefficients on the RMS of introduced noise for localized corrosion damage 20...60%.

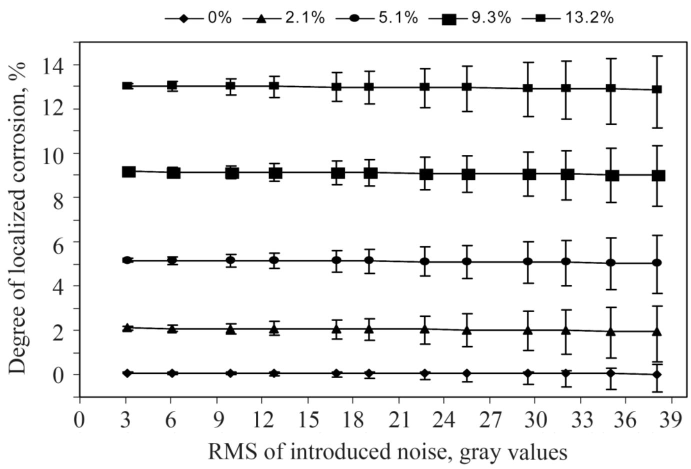

Fig. 12. Dependence of averages of evaluated degree of localized corrosion on the RMS of introduced noise for localized corrosion damage 0…13% .

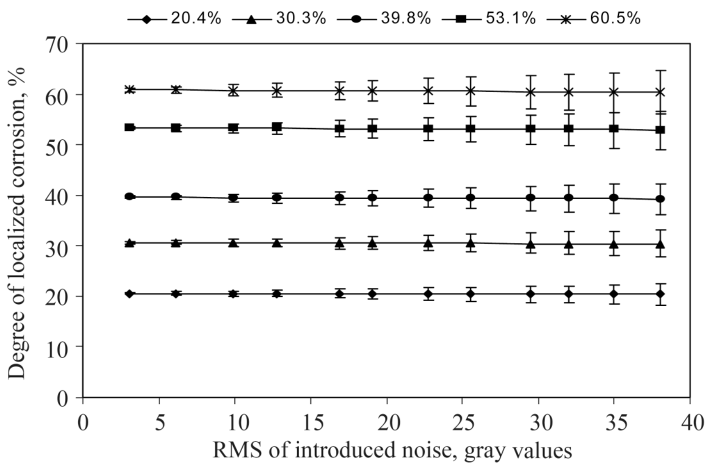

Fig. 13. Dependence of averages of evaluated degree of localized corrosion on the RMS of introduced noise for localized corrosion damage 20…60%.

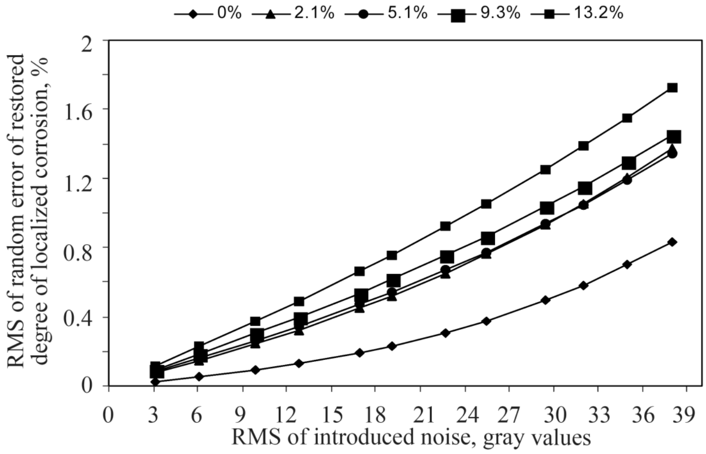

Fig. 14. The RMS of random error of evaluated degree of localized corrosion vs the RMS of introduced noise for localized corrosion damage 0…13%.

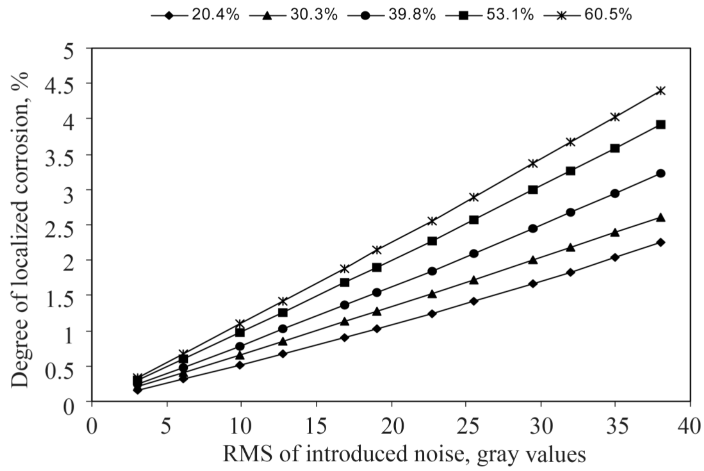

Fig. 15. The RMS of random error of evaluated degree of localized corrosion vs the RMS of introduced noise for localized corrosion damage 20…60%.

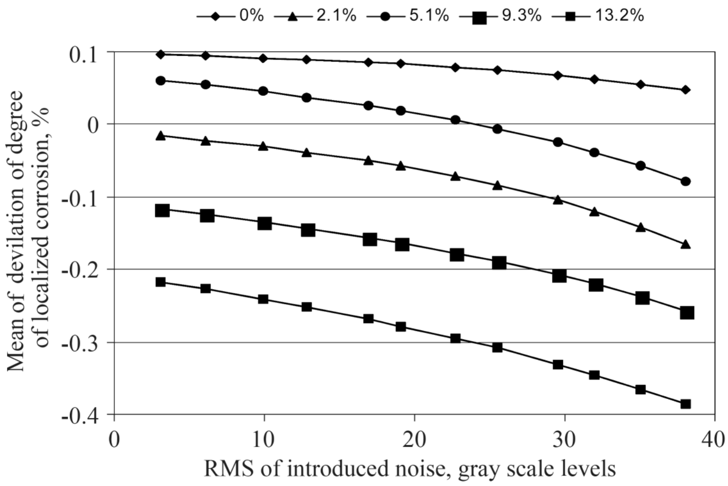

Fig. 16. Difference between averages of the evaluated degree of localized corrosion and exact introduced values for localized corrosion damage 0…13%.

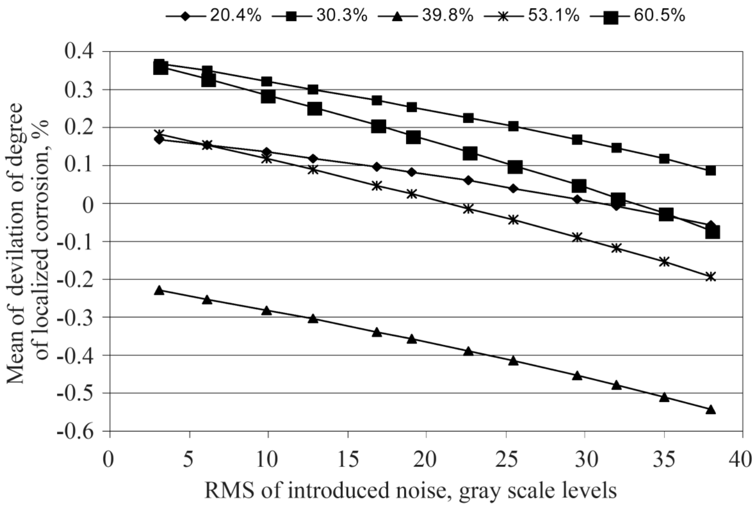

Fig. 17. Difference between averages of the evaluated degree of localized corrosion and exact introduced values for localized corrosion damage 20…60%.

CONCLUSIONS

Calibration and analysis of the inaccuracy of the proposed correlation-based measurement technology for the evaluation of the degree of localized corrosion explains its potential efficiency, even in the case of application of the middle-level hardware equipment. As it is shown, it can operate in a wide range of corrosion damage values 0...60% and the RMS of the input noise variations – up to 38 of gray scale values. That makes it attractive for the development of practically applicable correlation-based corrosion monitoring technologies. The proposed technology will be most effective in the case of low values of corrosion damage and high noises, where widely used video inspection systems are not accurate enough. Similar analysis and calibration can be easily used for the survey systems with other optical or resolution parameters. As it is seen, such measurement technology does not require high range of input speckle signal (above 256 gray scales), but can effectively reduce the influence of noise, for example light diffusion in corrosive (water) environment. Its accuracy is dependent on the choice of size of the sub-frame in a speckle image, where noise parameters are evaluated. Using the systems with higher resolution will allow providing data for more accurate evaluation and correction of the impact of noise, because a few of even unconstrained areas with arbitrary configuration shape can be selected on the input speckle image for this purpose.

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