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Prediction and evaluation on the transnational communication risk from the financial crisis based on the complex network

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Abstract. How to predict the financial development is the main problem faced in the researches on avoiding the financial risks. Currently, the auto-correlation function has obviously presented a limited capability in processing the empirical data related to the continuously-smooth finance, therefore, the complex network has been introduced to establish the new continuous and discontinuous covariance models thus to answer the problem why the financial market faces the negative interest rate, periodic falling and other difficulties, which is more flexible with powerful functions. Besides, it is defined through the topology based on the soft regularity-based conditional covariance, which makes it suitable for the asymptotic regression problem based on the monotone increasing domain, the Kriging method and the financial problems. The experiment result shows that the proposed method performs better in predicting the transnational communication risk from the financial crisis.

Key words. Complex network, Financial crisis, Transnational communication, Risk prediction.

1. Introduction

The real interest rate has become negative in many countries, which sometimes reaches to -2% and more, therefore, the European Central Bank has enlarged the stimulation, and the Bank of Japan and other several Central Banks have also implemented the same policy successively, which presents that the "zero lower bound" is just the boundary imagined by the traditional economists[1, 2]. The paper proves that the time evolution of the covariance is one of the reasons for the occurrence of the negative interest rate, wherein, the negative interest rate is generated because

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the interest rate increases the currency supply (basic currency deposit) thus to cause high currency supply while the "currency price" of the interest is very low. The evolution theory of covariance can explain why the negative interest rate can not be taken as the normal currency policy[3].

The dependency structure in the financial time series mainly refers to the covariance. The literature [4] points out one of the basic hypotheses related to the covariance function, wherein, the discontinuous covariance function has been applied in regression calculation and kriging[5, 6] recently, which, however, exists with flaws in its theoretical definition and performance research.In the computer experiment, the covariance function change is usually adopted to analyze the unilateral differentiable index decline based on the smooth Gauss. However, the non-smooth covariance conducts no research and design from the perspective of system application. Currently, the most important and most valued problems in the model include[7, 8]: (1) The improper application of the continuous covariance function; (2) The supervision of the positive definite covariance on the time evolution of the negative definite function. In the paper, the problems (1-2) are closely relevant. The existing literatures have proved that the real value can be replaced based on the following situations in the smooth Gauss process of the continuous related functions: the probability of the sample function being continuous is 1 or the probability of each finite internal being unbounded is 1. However, it is too strict for many practical statistical problems and people can not easily make judgement on the existence of the bounce in the observed routes: which is an ill-condition problem. The above-mentioned two extreme situations are impossible for the financial time series because the financial time series allows the price to exist with bounce[9]. In addition, any price continuity can not be proved from the perspective of theory because the close-range time point which is less than the Planck time unit can not be measured based on the physics theory, but instead, only the most numerable time point can be measured[10, 11].

Aiming at the above-mentioned problems, the paper introduces the class-based semicontinuous covariance complex network for substituting. To be more exact, it is a semivariance variable "continuous covariance" framework, especially the weak condition provided by the class for the covariance function, which causes the special class of the lagged asymptotic property of feasible domain increased in the semi-continuous mapping process, wherein, the regularity-based conditional covariance function can broaden the continuity condition.

2. Description of model

2.1. Semicontinuous covariance function

For the processing on the discontinuous Kriging interpolation, the semicontinuous covariance function based on the nugget effect is widely applied. In order to make the semicontinuous convariance function meet with the condition, consider to regulate the parameters such as the bounce c and the scope D, and then the covariance function $C(d)$ will be[12]:

$$C(d) = \begin{cases} \sigma^2, d = 0 \\ c\sigma^2, 0 < d \leq D \\ 0, else \end{cases} \tag{1}$$

Based on the parameters such as $c \in [0,1]$, D and $d \in [0,2]$, adjust the covariance function for form expansion, wherein, the σ^2 is the covariance parameter.

2.2. Semicontinuous covariance condition

Consider the isotropy-based smooth process[13, 14]:

$$Y(x) = \theta + \varepsilon(x) \ . \tag{2}$$

Take the points $x_1, x_2, \cdots, x_n$ from the impacted design space X, wherein, $Y(x)$ represents the measured value on the point x, and $\varepsilon(x)$ represents the error value on the point x. For the purpose of simplification, consider $X = [a, b]$ and assume the trend parameter $E(Y(x)) := \theta \in \Theta$ is unknown, and the latency covariance function $C(d)$ is determined by the unknown covariance parameter $r \in \Omega$, wherein, d_i refers to the relative lagging between the design point x_i and x_{i+1}. The parameter spaces of Θ and Ω are the open sets which are relative to the standard topology. In the finance, θ represents the stock price, x_i represents the time point, $Y(x_i)$ represents the monitoring value of the stock price on the time point x_i, which shows that the stock price change on the internal $X = [a, b]$ can be measured.

Definition 1: (condition) assume the class of the positive definite and measurable function $C(d)$: $\Omega \times R^+ \rightarrow R$, the condition will meet with the following features:

(a) If $r \in \Omega$, $C(0) = 1$;

(b) For r, the mapping $d \rightarrow C(d)$ is continuous;

(c) $\lim_{d \rightarrow +\infty} C(d) = 0$.

The above-mentioned contents define the conditions for the semicontinuous covariance function, wherein, the covariance can be increased or reduced as well as positive or negative. The paper conducts analysis on the topology convergence of the covariance function and proves that the function can be converged to be negative definite function.

2.3. Positive definiteness of covariance matrix

The following theorems explain the reasons for adopting the conditions from the perspective of geometric probability.

Theorem 1: assume C to be the continuous covariance, the covariance model can be defined as the bounce within specified time. Assume $t_1 < t_2 < \cdots < t_N$ to be N time points, which represents the evaluation time in the financial process based on the condition, and the probability of choosing $C^* = C$ will be 0, which means that choosing the continuous covariance is suitable for financial time series, because the autocovariance fitting presents better effect for the continuous and same data. Assume the three observation data points $t_1 < t_2 < t_3$, two positive point-point distances can be obtained : $d_1 = t_2 - t_1$, $d_2 = t_3 - t_2$. Consider the following condition: if $d_1 < d_2$, and there exists with bounce between the second and third observations, the following lemma will provide the necessary and sufficient condition constructed by the positive definite covariance condition.

Lemma 1: Make $C : [0, \infty) \to [0, \infty)$, $C(0) = 1$. If the time points $t_1, t_2, t_3 \in [0, \infty)$ meet with the condition of $t_1 < t_2 < t_3$, the mutual lagging can be represented as $d_1 = |t_1 - t_2|$, $d_2 = |t_2 - t_3|$ and $d_3 = |t_1 - t_3|$. Wherein, $d_3 = d_1 + d_2$, and then[15]:

$$D = \begin{vmatrix} 1 & C(d_1) & C(d_1 + d_2) \\ C(d_1) & 1 & C(d_2) \\ C(d_1 + d_2) & C(d_2) & 1 \end{vmatrix} . \tag{3}$$

If C is positive definite, $D \geq 0$. In addition, if the following condition can be satisfied:

$$C(d_1 + d_2) - C(d_1)C(d_2) \geq A/2 . \tag{4}$$

C_A will be positive definite on the time points t_1, t_2, t_3. And C_A should be positive definite when the determinant D_A wants to be the necessary and sufficient condition of the positive value.

$$D_A = \begin{vmatrix} 1 & C(d_1) & C(d_1 + d_2) - A \\ C(d_1) & 1 & C(d_2) \\ C(d_1 + d_2) - A & C(d_2) & 1 \end{vmatrix} . \tag{5}$$

Lemma 2: Make $C : [0, \infty) \to [0, \infty)$, $C(0) = 1$. If the time points $t_1, t_2, t_3 \in [0, \infty)$ meet with the condition of $t_1 < t_2 < t_3$, the mutual lagging can be represented as $d_1 = |t_1 - t_2|$, $d_2 = |t_2 - t_3|$ and $d_3 = |t_1 - t_3|$. Wherein, $d_3 = d_1 + d_2$, and then the form presented in the formula (2) can exist.:

If C is positive definite, $D \geq 0$. Reduce all element values of C when $A > 0$, namely, consider the function C_A to make it meet with the conditions of $C_A(d_1) = C(d_1) - A$, $C_A(d_2) = C(d_2) - A$ and $C_A(d_1 + d_2) = C(d_1 + d_2) - A$, and then the determinant D_A which is corresponding to the positive definite C_A will be as follows on the time points t_1, t_2, t_3:

$$D_A = \begin{vmatrix} 1 & C(d_1) - A & C(d_1 + d_2) - A \\ C(d_1) - A & 1 & C(d_2) - A \\ C(d_1 + d_2) - A & C(d_2) - A & 1 \end{vmatrix} . \tag{6}$$

For the condition of the determinant D_A being positive, its principal diagonal matrix of 2×2 should be negative definite, namely the condition should be:

$$1 - (C(d_1) - A)^2 < 0 . \tag{7}$$

Its sufficient condition for being positive definite is as follows:

$$\begin{cases} D_A - D > 0 \\ 1 - (C(d_1) - A)^2 \geq 0 \end{cases} \tag{8}$$

Next, adopt the covariance Ornstein-Uhlenbeck process to analyze the covariance model based on the lagged semicontinuous transformation method.

Theorem 2: Assume C to be the covariance model, $C(d) = \sigma^2 exp(-\psi_r(d))$. Wherein, the subfunction $\psi_r : [0, +\infty) \to R \cup \{+\infty\}$ is continuous and non-decreasing generator function, and $lim_{d \to +\infty} \psi_r(d) = +\infty$.

3. Improve the financial risk nodes based on the complex network

3.1. Model structure

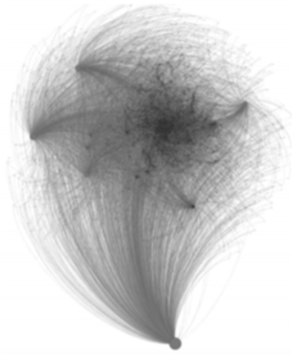
In recent years, the complex network theory has been applied in many fields of science, such as internet, neural network, social network, power network and network flow. The Americans Barabasi and Albert put forward the scale-free network model, namely BA network in short. The energy internet is a kind of small-world network, which is namely a kind of scale-free network needing to experience more complex process for formation in reality and base on several mechanisms for network simulation. Therefore, for the purpose of guaranteeing the better effect of the simulative network, it is needed to consider more practical factors, detailed steps and methods. The visualized results of the two kind of network topologies can be shown in figure 1.

Based on comparison in the model structure, the complex and mixed network model is similar to the internet in the structure, which is featured with node distribution and hookup distance. The formation of the simulation model can provide more reliable basis for the node distribution and node energy setting[13]. Currently, few researches on the distance between the nodes in the complex network have been conducted, and most financial risks are caused in the transmission process between different nodes. Besides, the financial risk increases with the increasing of the node distance, meanwhile, the topology model of the node affects the distance between different nodes to some extent.

3.2. Improvement model

Before introducing the improvement on the financial risk node model based on the complex network, firstly deduce and simplify the MINLP model in the formula (4), which can be presented as follows:

$$z = \sum_{l=1}^{C} \left[\left(\begin{array}{c} \sum_{i=1}^{N} \sum_{j=1}^{N} a_{ij} x_{il} x_{jl} \\ -\lambda \sum_{i=1}^{N} \sum_{j=1}^{N} a_{ij} x_{il} \end{array} \right) \Big/ \sum_{j=1}^{N} x_{il} \right]. \tag{9}$$



(a) Partial internet model topology

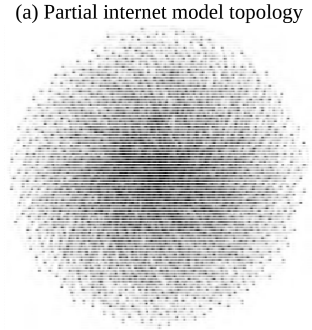


Fig. 1. Visualized results of the two kind of network topologies

After simplification, the adjustment coefficient λ is negative, which shows that the model can be the maximum edge number of each financial risk evaluation. When inspecting the larger financial risk node, set λ to be bigger to make punishment on the boundless node, correspondingly, make $\lambda \to 0$ when inspecting the smaller financial risk node. Even if the model can solve the problem through seeking for the optimal λ, consider $\lambda = 0.5$ for the purpose of simplification.

It can be seen from the above model that the correct number C^* of the financial risk node based on the complex network should be known in order to solve problems by aid of the model, but in fact, C^* can not be known in reality. Aiming at this problem, a substitute scheme is raised in this part, namely the upper bound value $C_{\max}$ based on the financial risk. Because each financial risk node contains three nodes at least, it can be known that $C_{\max} = N/3$, and the correct scope of the financial risk change is $C^* = 2 \sim N/3$. When $C^* < C_{\max}$, there is likely to exist with the financial risk without any nodes, namely the denominator $\sum_{j=1}^{N} x_{il} = 0$ in the simplification formula (9), which is not allowed. Therefore, set the binary variable b_1, if the number of the financial risk node is 0, $b_1 = 1$, otherwise, $b_1 = 0$. The improvement model can be defined as:

$$z = \max \sum_{l=1}^{C} \left[\left(\begin{array}{c} \sum_{i=1}^{N} \sum_{j=1}^{N} a_{ij} x_{il} x_{jl} \\ -\lambda \sum_{i=1}^{N} \sum_{j=1}^{N} a_{ij} x_{il} \end{array} \right) \Big/ \left(\sum_{j=1}^{N} x_{il} + b_1 \right) \right]. \qquad (10)$$

3.3. Estimation on the sampling probability distribution

The core idea of the estimation of distribution algorithms (EDA) is how to establish the probability model as well as the learning and sampling mechanisms more effectively. But the traditional EDA exists with two kinds of defects: one is the limitation in dimensionality, namely the high dimensionality exists with high coupling; another is no supervision in learning and non-ideal algorithm precision. Therefore, the paper designs the improvement mode of EDA based on the sampling probability model.

Assume X is the high-dimensional random vector and its joint probability density is $f_X(x)$, no modelling can be established directly owing to its feature of random irregularity. The solution relies on the modeling of its probability distribution $f_{X_i|X^{(i)}}\left(x_i\left|x^{(i)}\right.\right)$. The algorithm framework is shown in figure 2.

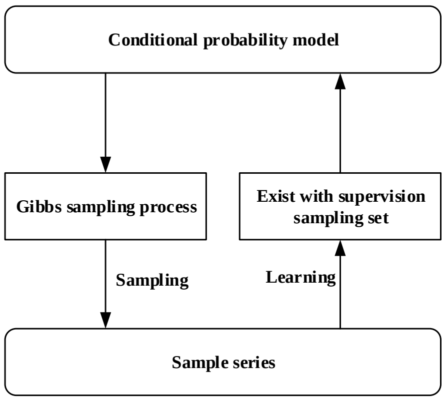


Fig. 2. Sampling probability model

The conditional probability distribution $f_{X_i|X^{(i)}}\left(x_i\left|x^{(i)}\right.\right)$ with the form of Markov chain can be established based on the above-mentioned Gibbs sampling thus to realize the increasingly approximating effect of the joint probability distribution $f_X(x)$.

In specific, the Gibbs sampling process refers to that a new individual generates randomly in each variable based on its conditional probability and population variable distribution thus to obtain the sample series with the form of Markov chain, and then the stable distribution of the conditional probability can be increasingly approximated based on the joint probability distribution of the sample series, namely use the time average to approximate to the statistics average $\varphi(X)$, the mathematical expression can be shown as follows:

$$\lim \sum_{t=1}^{T} \varphi\left(X\left(t\right)\right) \Big/ T = E\left\{\varphi\left(X\right)\right\} . \tag{11}$$

The above formula represents the sample series with the form of Markov chain, which is same to the sample set obtained from joint distribution. The pseudocode such as pseudocode 1 of the Gibbs sampling process algorithm is shown as follows.

Pseudocode 1: Gibbs sampling

Input: N, $P\left\{X_i\left|X^{(i)}\right.\right\}$;

2. Initialize the sampling process:

   $P=\emptyset, x\left(0\right)\sim Uniform\left(S\right);$

3. Carry out the iterative process:

   for $t=1\sim\left(K_0+N\right)$ ***do***

   for $i=1\sim D$ ***do***

   $x_i\left(t\right)\sim P\left(X_i\left|x_1\left(t\right),\cdots,x_{i-1}\left(t\right),x_{i+1}\left(t-1\right),\cdots,x_D\left(t-1\right)\right.\right);$

   endfor

   endfor

4. Output the result

   if $t>K_0$ ***then*** $P=P\cup\left\{x\left(t\right)\right\};$

Make $\Delta t=D$ in the pseudocode to make sure that each component will experience one Gibbs sampling process. The computation complexity in the above-mentioned Gibbs sampling process is $O\left(\left(D^2+N\right)\cdot D\right)$.

4. Experiment analysis

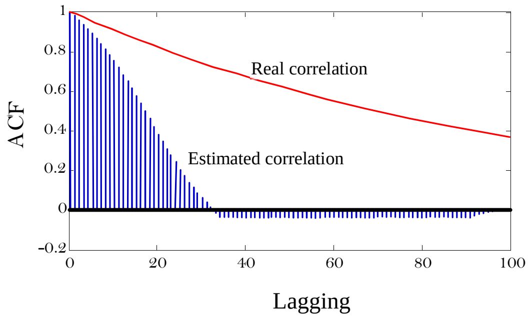
Conduct analysis on the influence of the R analysis software package on the model parameter, when the distance between the two time points Δt=1 in the discrete parameter interval [1,100], consider the following random walk form:

$$Y_t=\sum_{i=1}^{t}x_i, for\ t\in T\,. \tag{12}$$

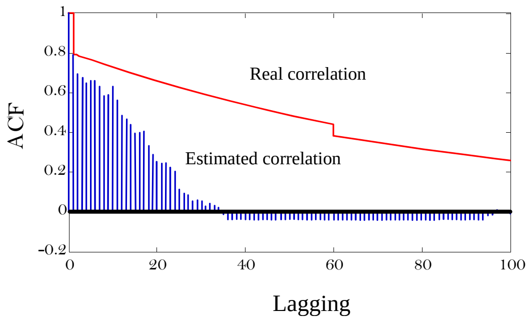
$$x=\left(x_1,x_2,\cdots,x_t\right)\sim\mathcal{N}(0,\sum)\,. \tag{13}$$

$$C(d)=e^{-d}\,. \tag{14}$$

The figure 3 presents the autocorrelation theory and its estimation based on the R analysis software, obviously, the traditional software makes non-full consideration on the real semicontinuous function model and its visibility. It can be seen from the drawn autocorrelation function based on the theory and experience by aid of the R analysis software that the real autocorrelation based on experience exists with serious underestimation.



(a) Continuous covariance autocorrelation function based on experience



(b) Two-bounce covariance autocorrelation function based on experience (r = 0.01)

Fig. 3. Estimation on the autocorrelation based on experience

Statistics definition and testing:

$$T = \sum_{t=0}^{n-1} \left| \rho\left(L\right) - \hat{\rho}\left(L\right) \right|. \tag{15}$$

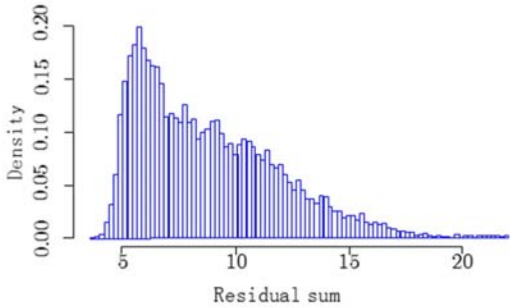
Calculate the absolute residual sum in figure 3 and know the continuous covariance data (figure 4a) is 63.4 and the two-bounce covariance estimation data (figure 4b) is 48.9. It can be seen from figure 4 that the covariance existing with bounce has smaller residual sum. The bounce point exists with certain difference with the bounce height c while the covariance should remain to be positive semidefinite.

Next, conduct analysis on the correlation of the two-bounce or the three-bounce by aid of the T histogram, wherein, the parameters r and n as well as the bounce point are set previously. Assume the parameter c comes from even distribution, $c_1 \in [0,\ 1]$, $c_2 \in [0, c_1]$ and $c_3 \in [0, c_2]$, and the result can be shown in figure 4.

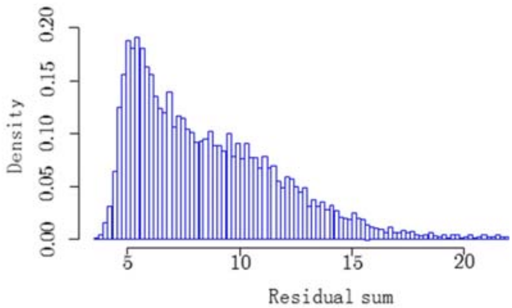
It can be seen from figure 4 that the larger the sum of all bounces in the discontinuous covariable is, the larger the T analysis value is, namely the larger the theoretical and empirical correlation difference is.

Conduct simulation experiment to verify how the condition improves the prediction result. Figure 5 shows the stock price change trend of one company in recent 90 days with the purpose of predicting the stock price in the future 10 days.

The curve in figure 5 shows the predicted result of the stock price based on



(a) Residual sum of two-bounce



(b) Residual sum of Three-bounce

Fig. 4. Analysis on correlation

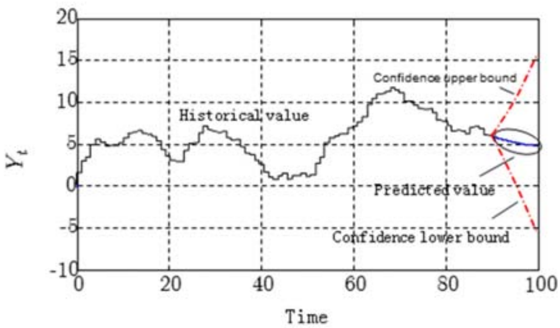


Fig. 5. Prediction on the stock price in the confidence interval of 95%

the continuous covariance and confidence interval. In the real finance, it is needed to estimate the parameters R and C and test whether the covariance exists with continuity. Because the parameters of the simulation examples are known and fixed. When the parameter r=0.1, there exists with two bounce points: (1) When the parameter $c_1 = 0.9$, it is in the place of latency 1; (2) When the parameter $c_2 = 0.8$, it is in the place of latency 30. Therefore, the covariance exists with no continuity.

Determine the predicted value of the future stock price based on dynamic simulation. Firstly,when the correlation variable x_i is transformed into the random variable $z_i = A^{-1}(x_1, x_2, \cdots, x_{90})'$ with the form of standard and normal distribution, $AA' = \sum$. Besides, the matrix A corresponds to the lower triangular matrix under the Cholesky decomposition. For one random prediction, the vector z is completed by 10 standard and formal random numbers and is transformed into correlative random variable by aid of $x_i^* = A^*(z_1, \cdots, z_{90}, z_{91}^*, \cdots, z_{100}^*)$. And the covariance matrix must use correct dimensionality. Carry out the above predicted process for 10000 times, the confidence interval $(1 - \alpha)$ shown in figure 6 can be obtained, wherein, the imaginary line refers to the predicted value and the dash-dotted line confidence boundary. Obviously, the condition adopted can provide wider prediction interval for the future price evolution.

5. Conclusion

The paper puts forward a kind of financial risk semicovariance model based on correlative error regression and introduces the complex network to establish the new continuous and discontinuous covariance models, which are defined through the topology based on the soft regularity-based conditional covariance and suitable for the asymptotic regression problem based on the monotone increasing domain, the Kriging method and the financial problems. Finally, based on the empirical analysis, the proposed method can predict the transnational communication risk from the financial crisis effectively, enhance the precision of numerical prediction and verity the effectiveness of algorithm.

References

[1] D. S. Abdelhamid, Y. Y. Zhang, D. R. Lewis, P. V. Moghe, W. J. Welsh, and K. E. Uhrich: *Tartaric Acid-based Amphiphilic Macromolecules with Ether Linkages Exhibit Enhanced Repression of Oxidized Low Density Lipoprotein Uptake*, Biomaterials *53* (2015), 32–39.

[2] X. Sun, Y. Xue, C. Liang, T. Wang, W. Zhe, G. Sun, X. Li, X. Li, G. Liu: *Histamine Induces Bovine Rumen Epithelial Cell Inflammatory Response via NF-κB Pathway.* Cellular Physiology & Biochemistry *42* (2017), No. 3, 1109–1119.

[3] N. Arunkumar, V. S. Balaji, S. Ramesh, S. Natarajan, V. R. Likhita, S. Sundari: *Automatic detection of epileptic seizures using independent component analysis algorithm.* IEEE-International Conference on Advances in Engineering, Science and Management, ICAESM-2012, art (2012) No. 6215903, 542–544.

[4] Y. Du, Y. Z. Chen, Y. Y. Zhuang, C. Zhu, F. J. Tang, J. Huang: *Probing Nanostrain via a Mechanically Designed Optical Fiber Interferometer.* IEEE Photonics Technology Letters *29* (2017), 1348–1351.

[5] S. L. Fernandes, V. P. Gurupur, N. R. Sunder, N. Arunkumar, S. Kadry: *A novel nonintrusive decision support approach for heart rate measurement.* Pattern Recognition Letters. https: //doi.org/10.1016/j.patrec.2017.07.002 (2017).

[6] N. Arunkumar, K. Ramkumar, V. Venkatraman, E. Abdulhay, S. L. Fernandes, S. Kadry, S. Segal: *Classification of focal and nonfocal EEG using entropies.* Pattern Recognition Letters *94* (2017), 112–117.

[7] J. W. Chan, Y. Y. Zhang, and K. E. Uhrich: *Amphiphilic Macromolecule Self-Assembled Monolayers Suppress Smooth Muscle Cell Proliferation*, Bioconjugate Chemistry *26* (2015), No. 7, 1359–1369.

[8] M. P. Malarkodi, N. Arunkumar, N., V. Venkataraman: *Gabor wavelet based approach for face recognition*. International Journal of Applied Engineering Research *8* (2013), No. 15, 1831–1840.

[9] L. R. Stephygraph, N. Arunkumar: *Brain-actuated wireless mobile robot control through an adaptive human-machine interface.* Advances in Intelligent Systems and Computing *397* (2016), 537–549.

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