D. Haase, E.-S. Wacker, E. G. Schukat-Talamazzini, J. Denzler. **Analysis of Structural Dependencies for the Automatic Visual Inspection of Wire Ropes**. *Proceedings of the 15th International Workshop on Vision, Modelling, and Visualization (VMV 2010)*. 2010. 49–56.

DOI: 10.2312/PE/VMV/VMV10/049-056.
The definite version is available at http://diglib.eg.org.

Analysis of Structural Dependencies for the Automatic Visual Inspection of Wire Ropes

D. Haase, E.-S. Wacker, E. G. Schukat-Talamazzini and J. Denzler

Institute of Computer Science
Department of Mathematics and Computer Science
Friedrich Schiller University of Jena, Germany

Abstract

Automatic visual inspection is an arising field of research. Especially in security relevant applications, an automation of the inspection process would be a great benefit. For wire ropes, a first step is the acquisition of the curved surface with several cameras located all around the rope. Because most of the visible defects in such a rope are very inconspicuous, an automatic defect detection is a very challenging problem. As in general there is a lack of defective training data, most of the presented ideas for automatic rope inspection are embedded in a one-class classification framework. However, none of these methods makes use of the context information which results from the fact that all camera views image the same rope. In contrast to an individual analysis of each camera view, this work proposes the simultaneous analysis of all available camera views with the help of a vector autoregressive model. Moreover, various dependency analysis methods are used to give consideration to the regular rope structure and to deal with the high dimensionality of the problem. These dependencies are then used as constraints for the vector autoregressive model, which results in a sparse but powerful detection system. The proposed method is evaluated by using real wire rope data and the conducted experiments show that our approach clearly outperforms all previously presented methods.

Categories and Subject Descriptors (according to ACM CCS): I.5.2 [Pattern Recognition]: Feature Evaluation and Selection, I.5.4 [Pattern Recognition]: Computer Vision

1. Introduction

Today, wire ropes are an inherent part of extraction technology, ship technology, bridge construction, lift systems or ropeways, to name but a few [DIN05]. For this reason, they have to meet highest safety standards and are subject to regular inspections [WMW03, DIN05]. These inspections are carried out by the human expert and have several drawbacks, like the exposure to physical dangers or atmospheric conditions [WMW03]. Additionally, this is a very monotonous task, which provokes a loss of concentration and leads to missed defects.

For this reason, an automatic inspection of wire ropes is desirable. A first step in this direction is made by [WMW03], who present a prototype system for the visual acquisition of wire ropes with the use of four line cameras which are placed in steps of 90° around the wire rope. However, the automatic inspection is not an easy task, as most defects like wire fractions, missing wires or changes in the rope structure are very inconspicuous. Furthermore, wire ropes are often soiled by water, oil or mud, which complicates an automatic inspection even more. An illustration of above mentioned wire rope defects can be found in the left column of Figure 1.

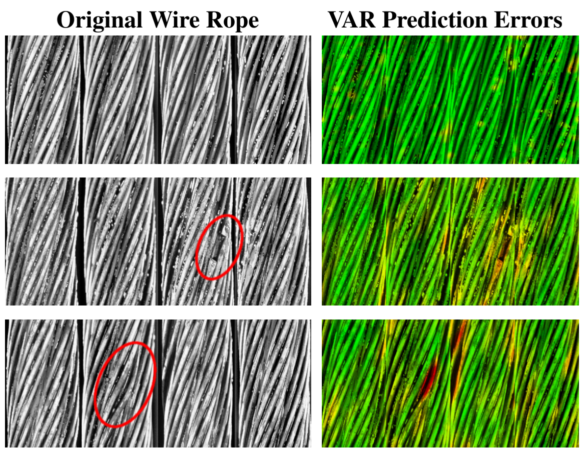

Figure 1: *Visualization of the vector autoregressive (VAR) prediction errors (right column) for three wire rope segments (left column). For each segment, the four camera views are shown side by side as they are represented in the data matrix* $\boldsymbol{Y}$*. Faults in the original wire rope are marked with a red ellipse. For the predictions, green color represents a small, red color a large absolute error.*

1.1. Related Work

Due to the high security standards, only very few samples of defective wire rope data are available in general, for which reason one-class classification or anomaly detection [Tax01] approaches have to be applied. One-class classification is widely used in texture and surface analysis, for which [Xie08] provides a recent review. With regard to the methods used in this paper, especially time series based models are of interest. However, most works in the field of anomaly detection in time series data are designed for univariate time series. Multivariate approaches are presented by [BB07] or [CTPK09], but are not applicable in the present case because of the large dimensionality of the wire rope data. Two-dimensional autoregressive models are used by [STAR01] for the detection of microcalcifications in mammograms, whereas [BSUL04] employ multivariate autoregressive models and use the model parameters as features for a detection of defective regions in multivariate time series data.

Methods for the defect detection in wire ropes based on the prototype system of [WMW03] are presented in [PNWD09]. It is based on a Hidden Markov Model [Rab89], which is used to model the intact wire rope data. Defective regions are then detected by using the quotient of two consecutive Viterbi scores as anomaly indicator. The main drawback of this method is that each camera view is analysed separately, for which reason no contextual information between the camera views is taken into account for the defect detection.

1.2. Our Approach

The main idea we base our approach on is the combined analysis of all camera views. This strategy allows us to take advantage of the strong dependency relations between the camera views which are to be expected due to the regular wire rope structure. For this reason, the open questions are whether the usage of this extended context information leads to a substantial increase of detection performance and how the additional context is to be included into the defect detection system. To answer these questions, a suitable model is needed which allows for a one-class classification approach. Basically, time invariant or time variant methods can be used for this task. Based on the nature of the camera acquisition system and the general structure of the wire ropes, it seems more promising to employ time-variant methods. These can be differentiated into univariate and multivariate models. Due to the expected feature dependencies implied by the wire rope structure, multivariate approaches are to be preferred.

Considering all requirements for the model used in this work, vector autoregressive (VAR) models [Lüt93] remain as the method of choice for potential improvements based on the additional context information of all camera views.

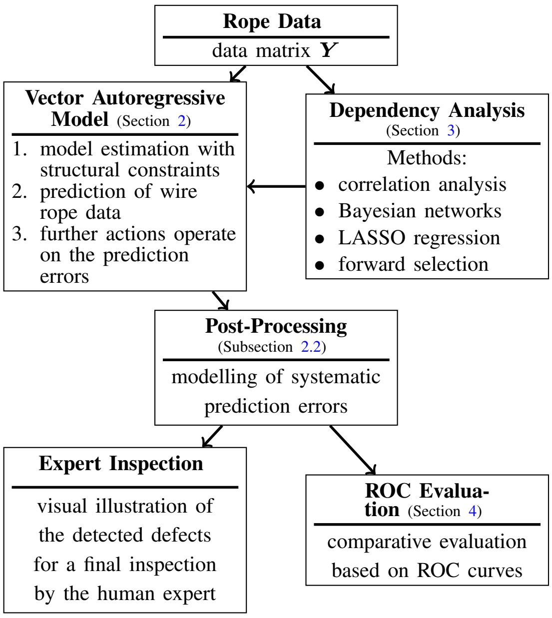

Figure 2: *Schematic model for the defect detection in wire ropes based on VAR models with structural constraints as proposed in this paper.*

They are suited to answer the most important open questions and allow for a simultaneous analysis of all camera views in an easy way because of their vector character. Additionally, the expected dependencies in the wire rope data may easily be integrated as constraints into the model, as we will show in the following section. These constraints allow the VAR model to operate on much higher dimensional data than previous approaches. As the computational complexity for the estimation of VAR model parameters is cubic in the total number of explanatory variables, a typical reduction of the possible explanatory variables to 2.5% of the original amount results in a speed-up factor of $6 \cdot 10^4$ or a $1/0.025 = 40$ times higher amount of actually used explanatory variables. Additionally, by using constrained VAR models, the results tend to be more robust because of the filtered out noise influences.

The above described schematic procedure for the application of constrained VAR models for the defect detection in wire rope data is shown in Figure 2. The remainder of this paper is structured as follows: the essential VAR models are described in Section 2. Methods for the dependency analysis in real wire rope data are presented in Section 3. Finally, the experimental results are discussed in Section 4.

2. Vector Autoregressive Models for Defect Detection

Autoregression [Job91] aims at modelling the interrelationships between a target variable y_t and the p explanatory variables $y_{t-1}, \ldots, y_{t-p}$ of a time series $(y_t)_{1 \leq t \leq T}$ by means of a regression function f. It is characterized by the relation $f(y_{t-1}, \ldots, y_{t-p}) = \mathbb{E}\left[y_t \mid y_{t-1}, \ldots, y_{t-p}\right]$, where $\mathbb{E}\left[\cdot \mid \cdot\right]$ denotes the conditional expectation. Typically, f is defined to be a linear function with parameters $c, \phi_1, \ldots, \phi_p$. Taking into account that generally $f(X)$ does not exactly match the actual value of y_t, an error term ϵ_t has to be considered and an autoregressive model of order p may be written in the form

$$y_t = c + \sum_{q=1}^{p} \phi_q y_{t-q} + \epsilon_t. \qquad (1)$$

A VAR model [Lüt93] is the multivariate extension of the model above. If we replace all scalars y_t, c and ϵ_t by N-dimensional vectors and the coefficients $\phi_1, \ldots, \phi_p$ by $N \times N$ matrices $\mathbf{\Phi}^{(1)}, \ldots, \mathbf{\Phi}^{(p)}$, we get the VAR model

$$\boldsymbol{y}_t = \boldsymbol{c} + \sum_{q=1}^{p} \mathbf{\Phi}^{(q)} \boldsymbol{y}_{t-q} + \boldsymbol{\epsilon}_t. \qquad (2)$$

The elements $\boldsymbol{y}_t = [y_{t,1}, \ldots, y_{t,N}]^{\mathrm{T}}$ of the underlying time series can be combined into the data matrix $\boldsymbol{Y} = [\boldsymbol{y}_1, \ldots, \boldsymbol{y}_T]^{\mathrm{T}}$. For the representation of wire rope data as a data matrix, every camera line corresponds to a time index t. In this way, all four camera views can be easily combined by concatenating the data of these line cameras to the vector $\boldsymbol{y}_t$ for each time index t. Using this approach, the VAR model is capable of covering the influences between different camera views because of its vector character. Three examples for wire rope data matrices are given in the left column of Figure 1.

Generally, parameter constraints for VAR models may be arbitrarily complex, but for the present case of wire rope data, binary structure constraints are sufficient. These binary constraints only regulate which influences of the VAR model variables are to be allowed at all and which are not. This is motivated by the regular rope structure, which suggests a strong dependency structure for the elements of the wire rope data, too.

We base the parameter estimation for such constraints on the result of [Zel62], who shows that the multivariate least-squares estimation of the VAR model parameters may be performed separately for all its vector components using ordinary least squares (OLS) estimation. Thus, instead of considering one regression problem with the target variable $\boldsymbol{y}_t$, it is sufficient to solve N scalar regression problems with the target variables $y_{t,n}$ for $1 \leq n \leq N$. Note that the set of potential explanatory variables nevertheless is equal in both cases. With this result, the estimation with binary parameter constraints may be realized by simply neglecting respective components of the explanatory vectors for each of the N regressions.

2.1. Application for Defect Detection in Wire Ropes

As already mentioned, only few samples of defective wire rope segments are available in the present case, for which reason we base our approach on the concept of one-class classification. The detection of defects has to be entirely based on the usage of intact wire rope data. In addition to the methods proposed in the literature, also constrained VAR models can be used for this task, whereas our approach is as follows: at first, the binary parameter constraints are determined using faultless wire rope data. The according methods are discussed in Section 3. Afterwards, the VAR model parameters are estimated on a different, but also faultless part of the wire rope data. With these estimated model parameters, a prediction $\hat{\boldsymbol{y}}_t$ of $\boldsymbol{y}_t$ can be obtained based on Equation (2). As the model parameters are learned exclusively on intact wire rope data, it is to be expected that defective rope segments can not be described well by the model. Therefore, significant prediction errors $\boldsymbol{e}_t = \boldsymbol{y}_t - \hat{\boldsymbol{y}}_t$ are to be expected for faulty rope segments.

It is possible to preselect and visualize these prediction errors for the human expert for a final inspection. As only few faults are to be expected in each wire rope, this procedure is capable of filtering out the vast majority of obviously faultless segments while still leaving the final decision to the human expert for doubtful rope segments. Additionally, the exact location of the detected defects can be shown on the surface of the wire rope, which is a vast advantage compared to previous approaches. An example of a possible visualization of the VAR prediction errors is shown in Figure 1 for one intact and two faulty rope segments. It depicts the original wire rope in the left column and the respective prediction errors of the underlying constrained VAR model in the right column. Green color indicates a small, red color a large absolute prediction error. It can be seen that the faultless segment has small prediction errors, whereas the real wire rope defects cause obvious prediction errors at the appropriate locations.

For the reason of a comparison with other approaches and to allow a qualitative evaluation, we additionally use the common method of receiver operating characteristics (ROC) analysis [Faw06]. As ROC analysis operates on a series of scalar values (scores) and the labeling in the ground-truth data is based on camera lines, the prediction error vectors $\boldsymbol{e}_t$ have to be mapped to scalars s_t for each camera line t.

If we denote the elementwise absolute values of a vector by $|\cdot|$ and compare the vectors $|\boldsymbol{e}_{t_1}|$ and $|\boldsymbol{e}_{t_2}|$ corresponding to a time index t_1 of a real wire rope defect and to a time index t_2 of an intact wire rope segment, respectively, one striking difference is to be expected: as faulty regions appear only locally in the wire ropes, the vector $|\boldsymbol{e}_{t_1}|$ should have a local peak. In contrast, the vector $|\boldsymbol{e}_{t_2}|$ is expected to have no evident peak but a rather regular pattern. Therefore, we employ the Fourier transform to calculate the score s_t for each prediction error vector $\boldsymbol{e}_t$, as it is capable of distinguishing between such faulty and intact wire rope segments. However, as the Fourier transform does not perform a dimension reduction, we need to select the necessary information for the score s_t from the Fourier transformed vector $|\boldsymbol{e}_t|$. We achieve this by analysing the Fourier coefficients according to their ability to separate faulty and intact wire rope segments and finally using the Fourier coefficient which allows the best separation as score s_t for each time index t. In tests based on real wire rope data, we ascertained that the first Fourier coefficient enables the best separation. This is a very favourable result which substantially simplifies the calculation for each score s_t, as the first Fourier coefficient corresponds to the mean value of the vector $|\boldsymbol{e}_t|$, and we obtain

$$s_t = \frac{1}{N}\sum_{n=1}^{N}|e_{t,n}| = \frac{1}{N}\sum_{n=1}^{N}|y_{t,n} - \hat{y}_{t,n}|. \qquad (3)$$

Motivated by the fact that in the present wire rope data sets the faulty camera lines are labeled with a large margin around the actually visible parts of the defects, a smoothing of the scores along the camera lines may also be applicable.

2.2. Problems

The very specific nature of wire ropes causes some problems in practical applications, which are described below together with our solutions to deal with these effects.

As the border regions of the camera views generally do not allow a reasonable defect detection, we exclude them from the detection task, as can be seen in the left column of Figure 1.

Another issue for wire rope data has a more theoretical background. It can be easily shown, that wire rope data emerge from non-stationary processes, which means that for the random variable $\boldsymbol{y}_t$ mean and variance change for different time indices t. As a consequence, systematic prediction errors occur in the predictions of the VAR model [Lüt93]. In the time series of the prediction error vectors this becomes manifest in a faint but regular pattern, which roughly follows the original structure of the wire rope. It is desirable to filter out this regular pattern from the prediction errors to reveal the irregular part caused by real defects. For this purpose we employ the method of frequency domain self-filtering [Bai97], which yields excellent results in this context.

The third and probably most striking concern regarding the usage of VAR predictions for wire rope data is the problem of self-prediction. Ideally, the wire rope has a perfectly periodic structure and each target variable $y_{t,n}$ can be predicted by arbitrarily distant explanatory variables. In real data, however, the ideal rope structure is disturbed by noisy influences like physical distortions. Therefore, the general predictability decreases with the physical distance between the target variable and the explanatory variables on the real wire rope. The OLS estimator will therefore always choose the VAR parameters in such a way that each target variable $y_{t,n}$ is only affected by its direct neighbours, as these allow the best prediction. Other explanatory variables are systematically disregarded. In the sense of least-squares estimation, this behaviour is absolutely correct, as these predictors allow the smallest prediction errors. However, for the defect detection this causes the unwanted effect that each defect of the wire rope predicts itself after a short period of time. Therefore, in the context of the special structure of wire ropes, the VAR parameter estimation is actually an ill-posed problem. To overcome this handicap, we exclude all potential explanatory variables within a certain range from the target variable from the regression. If, as before, p denotes the order of the VAR model, then we call $p_{\text{sep}} < p$ the size of this exclusion zone and $p_{\text{eff}} = p - p_{\text{sep}}$ the effective VAR model order. The potential explanatory variables for each target variable $y_{t,n}$ then reduce to $\boldsymbol{y}_{t-p_{\text{sep}}-1}, \ldots, \boldsymbol{y}_{t-p}$. Technically, this can be achieved by using binary constraints. We base the selection of p_{sep} on the wire rope structure, which has the advantage of allowing for an automatic calculation. It can be shown, that choosing p_{sep} to be the distance of two neighbouring wires in the direction of the time axis is sufficient to ensure multiple equally important explanatory variables for a target variable.

3. Analysis of Structural Dependencies

The goal of the structural dependency analysis is to reveal independencies between each target variable $y_{t,n}$ and the vector components of the explanatory variables $\boldsymbol{y}_{t-p_{\text{sep}}-1}, \ldots, \boldsymbol{y}_{t-p}$. This enables us to derive structural constraints for the VAR model which improves the prediction quality, makes the estimation process more robust and substantially reduces the high dimensionality of the problem. We will discuss how these constraints can be automatically obtained from wire rope data using various methods, including correlation analysis, Bayesian networks, LASSO regression and forward selection. For the following discussion, we denote the set of all possible explanatory variables for a target variable $y_{t,n}$ with

$$E_n = \{\, y_{t-q,m} \mid p_{\text{sep}} < q \leq p,\ 1 \leq m \leq N \}\,. \qquad (4)$$

3.1. Conditional Independence

For a theoretical discussion of the dependency analysis methods we need the concept of conditional independence [Daw79]. For three pairwise disjoint subsets U, V and W of a set of random variables we call U conditional independent of V given W if and only if $\mathbb{P}(U \mid V, W) = \mathbb{P}(U \mid W)$. In the following discussion we will denote this ternary relation by $U \perp\!\!\!\perp V \mid W$.

For the OLS estimation of the VAR model parameters for the target variable $y_{t,n}$, our goal is to find a partition of all explanatory variables E_n into the sets I_n and J_n for which $\{y_{t,n}\} \perp\!\!\!\perp I_n \mid J_n$ holds, as this implies

$$\mathbb{E}\left[y_{t,n} \mid I_n, J_n\right] = \mathbb{E}\left[y_{t,n} \mid J_n\right]. \qquad (5)$$

Therefore, if I_n and J_n are known, the potential explanatory variables from I_n can be entirely neglected for the regression without the loss of prediction quality.

The theoretically correct solution for this problem under the assumption of normal distributed data is the method of covariance selection. It was introduced by [Dem72] and theoretically confirmed by [Wer76]. However, this method is computationally very expensive and can not be applied on the high-dimensional wire rope data. Therefore, we have to apply approximate techniques, which are presented in the following.

3.2. Applied Methods

A very simple approximation approach is the correlation analysis [Rei93, Chapter 1]. In the case of wire rope data, it is based on the lagged cross-correlation coefficients $\rho_{n,m}(l) = \mathrm{Cor}\,(y_{t,n}, y_{t-l,m})$ of the underlying data matrix $\boldsymbol{Y}$. The set of explanatory variables J_n which are actually used for the regression is selected based on thresholding the absolute lagged cross-correlation values. This method is an approximation of the correct solution, because it can be shown that the weaker marginal independence is used instead of the conditional independence.

Another method we applied to obtain the sets I_n and J_n from wire rope data were Bayesian networks [Pea00]. They model the dependency relationships of random variables with the help of a directed acyclic graph, from which the desired independencies, the set I_n, may be easily extracted. One issue of Bayesian networks used on wire rope data is a degeneration effect, which emerges due to the fact that two geometrically adjacent features are very similar to each other. As a consequence, about 1–2 explanatory variables are selected for each target variable in total. This effect can be weakened by applying the method on the potential explanatory variables of each time step $p_{\mathrm{sep}} + 1, \ldots, p_{\mathrm{sep}} + p_{\mathrm{eff}} = p$ separately to increase the amount of total explanatory variables by the factor p_{eff}.

Also the LASSO (**L**east **A**bsolute **S**hrinkage and **S**election **O**perator) regression [Tib96] may be used to find dependency structures in wire rope data. While for the OLS estimation the expected quadratic prediction error $\mathbb{E}\left[(y_{t,n} - \hat{y}_{t,n})^2\right]$ is minimized without any further constraints, the LASSO regression uses the additional restriction

$$\sum_{q=1}^{p} \sum_{n=1}^{N} \sum_{m=1}^{N} |\boldsymbol{\Phi}_{n,m}^{(q)}| \leq u \tag{6}$$

for the model parameter matrices $\boldsymbol{\Phi}^{(1)}, \ldots, \boldsymbol{\Phi}^{(p)}$ and the regularization parameter $u \geq 0$. This constraint has the advantageous effect of causing many parameters to become exactly zero. Using this property, the set of unnecessary explanatory variables I_n may easily be derived, as it can be shown that these LASSO estimates are asymptotically correct in terms of conditional independence [FHT08].

Another possibility for the selection of a sparse set of predictors for a given target variable $y_{t,n}$ is the method of forward selection [HTF09, Chapter 3]. It belongs to the greedy algorithms and therefore specifies the set of optimal explanatory variables only approximately in general.

Examples for the resulting parameter structures of the methods used along with the original lagged cross-correlation matrices for real wire rope data are given in Figure A.1. Implied by the regular rope structure, the depicted lagged cross-correlation matrices show very characteristic patterns. Also, the extreme sparsity of the model when using Bayesian networks is obvious. The structure constraints obtained by the LASSO regression and the forward selection are very similar to each other, and most explanatory variables are chosen from the nearest and furthest possible temporal context for each target variable. A reasonable explanation for this effect is that the explanatory variables with the time index $t - p_{\mathrm{sep}} - 1$ carry all the necessary information of the times $t - p_{\mathrm{sep}} - 2, \ldots, t - p$ and have the smallest noise impacts due to their proximity to the target variable. For this reason, all other time indices are concealed by $t - p_{\mathrm{sep}} - 1$. In the same manner it can be argued that the time index $t - p$ conceals all remaining indices $t - p - 2, \ldots, 1$, resulting in the observed parameter structure.

4. Experiments

Numerous experiments have been carried out to investigate the practical performance of the presented approach. The method of evaluation are ROC curves and their corresponding area under the curve (AUC) values [Faw06]. Particularly we compare our model to the Hidden Markov Model approach of [PNWD09], as it yields the best results so far. Consequently, the same real ropeway data set as in [PNWD09] was used.

In the experiments, we concentrated on the performance of the various dependency analysis methods presented in Section 3. We used the grayscale values of the line cameras as underlying features, as these preserve the original dependency structure of the wire rope. Both the dependency analysis and the parameter estimation were carried out on the first $5 \cdot 10^4$ camera lines, which correspond to five metres of wire rope. All experiments were made on the entire wire rope with a length of $13.6 \cdot 10^6$ camera lines corresponding to $1.3\,\mathrm{km}$. Based on the wire rope geometry we used $p_{\mathrm{sep}} = 40$. The effective VAR model orders were chosen to be $p_{\mathrm{eff}} = 20$, except for the LASSO regression, for which computational considerations made a reduction to $p_{\mathrm{eff}} = 5$ necessary. However, tests suggested that this reduction of the model order does not have a strong negative influence on the performance for the LASSO model parameters. The threshold for the correlation approach, the LASSO regularization parameter u and the variable count of the forward selection were chosen in such a way that the total number of explanatory variables for all N target variables was ap-

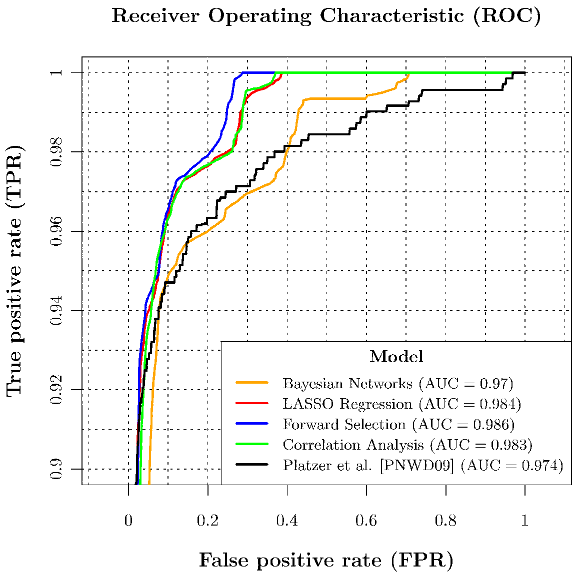

Figure 3: *ROC curves of the presented VAR-based defect detection model for various dependency analysis methods. The results of the model from [PNWD09] are included for a comparison. The experiments were performed on a real wire rope data set.*

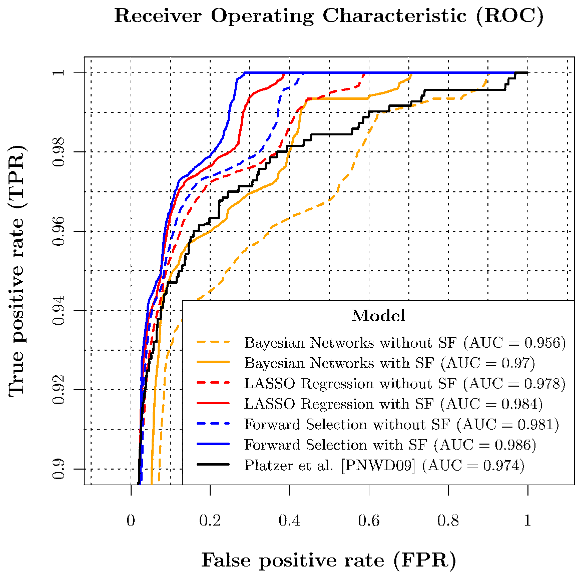

Figure 4: *ROC curves of the dependency analysis methods in comparison to the case without self-filtering. The results of the model from [PNWD09] are included for a comparison.*

proximately 2.5% of the original amount, which allows for a reasonable trade-off between computing time and detection performance. The resulting ROC curves and the corresponding AUC values are shown in Figure 3. As it is important to detect all wire rope defects in this security relevant application, only regions of the ROC curves with a true positive rate close to one are of interest. From this point of view, all approaches except for the Bayesian networks clearly outperform the approach of [PNWD09], as the false alarm rate for a true positive rate of 100% is reduced from 96% to 26%. The best results were achieved by the forward selection method, closely followed by the LASSO regression and the correlation approach. The comparatively weak performance of the Bayesian networks can be partly explained by the very small amount of explanatory variables caused by the degeneration effect when used on wire rope data.

Additionally, further experiments were made to investigate the effects of several other aspects on the detection performance. It became clear, for instance, that both the post-processing step of self-filtering as well as the smoothing of the camera line scores are crucial for the detection performance. In Figure 4, the ROC curves of the presented dependency analysis methods are shown in comparison to the case in which the self-filtering step was omitted. It can clearly be seen that the use of self-filtering causes a reduction of the false alarm rate of about 10% for a true positive rate of 100%. The influence of the self-filtering step is approximately equal for all presented dependency analysis methods, for which reason the ranking remains the same as for the case with self-filtering. Notably, even without self-filtering, our approach still outperforms the method of [PNWD09].

5. Conclusions and Outlook

We have presented a multivariate approach for defect detection in wire ropes. Earlier works are limited to a separate analysis of the camera views of a wire rope, while our approach allows for a simultaneous inspection of the underlying data. We employed various dependency analysis methods to take advantage of the structural dependencies in the data which are to be expected due to the regular wire rope structure. These dependencies were used as constraints for a vector autoregressive model. As a result of the structural constraints, the prediction quality was improved, the estimation process became more robust and the high dimensionality of the problem was substantially reduced. The corresponding VAR prediction errors were used as basis for the visualisation of the defect detection and the comparative ROC evaluation.

We compared correlation analysis, Bayesian networks, LASSO regression and forward selection as dependency analysis methods. The best results were obtained by using forward selection as dependency analysis method. Due to the degeneration effect in the context of wire rope data, Bayesian networks obtained the worst results. Especially the constrained VAR models based on forward selection and LASSO regression clearly outperformed competitive approaches [PNWD09]. In the context of security related applications with a desired true positive rate of 100%, the corresponding false positive rate could be reduced from 96% to

26% compared to [PNWD09]. Another advantage of our approach is the ability for an exact localization of the defects, which is not possible with previous methods.

Potential improvements of our approach may be achieved by enlarging the context of the VAR model while leaving the total number of prediction variables unchanged, which can be done by exploiting the special properties of the dependency analysis methods. A concrete example for the LASSO regression and the forward selection is the limitation on explanatory variables from two relative points in time, namely those two with the dense occupation of explanatory variables. Based on the experiments, this approach should sustain the detection performance but drastically decrease the computing time. Another interesting aspect is the inclusion of non-visual measurement data, for instance from magnetic inductive tests, to avoid a restriction on exterior defects.

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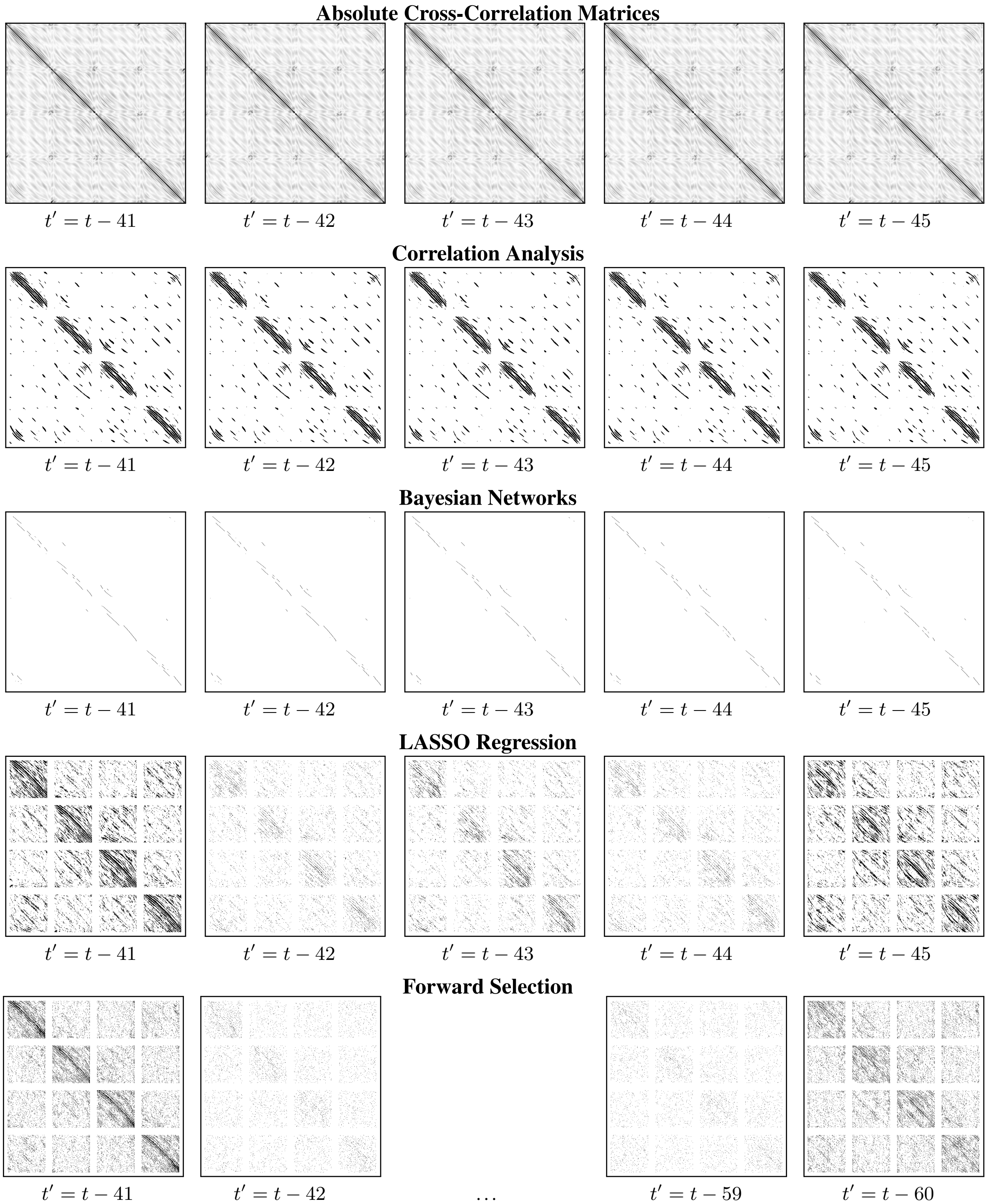

Figure A.1: *Structure constraints obtained with the presented dependency analysis methods from grayscale value features of a real wire rope data set. For these examples, the VAR model orders were chosen to be* $p_{\text{sep}} = 40$ *and* $p_{\text{eff}} = 5$*. For the forward selection method,* $p_{\text{eff}} = 20$ *was chosen. Each square depicts a* $N \times N$ *matrix, whereas the* n^{th} *row corresponds to the target variable* $y_{t,n}$ *and the* m^{th} *column corresponds to a potential explanatory variable* $y_{t',m}$*. Black entries represent actually chosen explanatory variables.*