Event Detection Using Multisensor Fusion and Filtering Techniques Based on CWT and SVM

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ABSTRACT

This paper investigates the use of multisensor data fusion principle to design an object detection system based on Support Vector Machine (SVM) for monitoring and supervision of a complex production process. The goal is to state the existence of undesired objects in the process or to detect events in streamed data. The monitoring system includes acceleration sensors used as sensor-cluster. In order to extract the relevant features of the acceleration signals, Continuous Wavelet Transform (CWT) is used along with other supporting algorithms. The extracted features of the individual sensors are undergone multistage filtration and fusion processes. These processes aim to reduce the false alarm rate as well as to realize a reliable decision about the presence of undesired objects.

INTRODUCTION

Supervision and monitoring tasks of industrial processes often uses thresholds for distinction of regular and abnormal system states to reduce the complexity and multidimensionality of the process parameters and measurements. In many applications the structure and dimensionality of the data available for fault detection and classification require more reliable tools to depend on and defining simple limits and threshold is considered in these cases unprofitable. Additionally, due to the complexity of the systems to be monitored, it is very complicated and often not helpful to realize model-based monitoring system which requires precise models of

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the considered mechanical system in order to perform a reliable monitoring task [1]. Model-based methods require usually a complex modeling of the process with detailed process parameters as well as additional information how the system states would be changed corresponding to considered changes. On the other hand, reliable signal-based approaches should include appropriate feature extraction methods to expose the indicators which are connected directly to the fault behavior and system state.

Depending on the complexity of the machines and processes, specific sensors have to be used and even suitable complex characteristics have to be defined to specify suitable mappings between operations related machine states and sensor data. Feature extraction progression is done either in time or frequency domain of the related signal (sensor data).

This paper investigates the use of multisensor data fusion principle to design an object detection system based on Support Vector Machine (SVM) [2] for monitoring a complex real industrial process. A feature extraction approach based on Continuous Wavelet Transform (CWT) [3] along with fused parallel individual classifiers is proposed. The goal is to recognize the existence of undesired objects in the production process on real-time basis. For the specific application the presence of undesired objects within transported material has to be detected (object present yes/no) to avoid later on resulting disturbances and failures during the continuously operating transportation process. The process includes several acceleration sensors mounted in different positions along the production and transportation process. In this case no sensor can detect the objects existence directly, therefore indirect measurements of the objects to be detected have to be used, be combined etc. to conclude implicitly to the existence of the undesired objects.

SYSTEM DESCRIPTION

The considered production process is used to remove and transport overburden. The overburden often contains unwanted objects of different sizes. The overburden is continuously discharged onto a conveyor belt and transported to specific places. Unwanted objects within the overburden could cause damage in the production system (such as longitudinal cracks or punctures on the conveyer belts, damage on the drive pulleys, etc.). Each damage or fault could lead to shutdown of the production system, leading to reductions of the capacity of the production as well as it increases the operating costs.

In this contribution four signals (here: acceleration signals) will be considered. An inevitable and varying time shift between the stimulation of the individual sensors of the process exists. This is due to the non-rigorous nature of the process which makes the fusion of the process information in the level of data and features difficult. Therefore the signal pre-processing, the feature extraction, the classification process, and the classifier adaptation process are applied to the individual information sources followed by a decision fusion module, which is based on specifically trained decision criteria to combine the individual decisions of the different classification modules. The combination should lead to more reliable information about the system state (object present yes/no).

WAVELET-BASED FEATURE EXTRACTION

The signal pre-processing and feature extraction aim to eliminate redundant information and to reform the included relevant information of the signal in a distinctive form in order to enable the classification of the system states.

In wavelet analysis, signals are decomposed into wavelets of varying durations. These wavelets represent, as an example, localized vibrations of a sound signal or localized variations of image details. Wavelets are used in a wide variety of signal processing tasks such as compression, removing noise, or enhancing recorded sound or image in various ways. Wavelets-based approaches are widely used in classification and recognition tasks as feature extraction tools [4]. The continuous wavelet transform (CWT) is an alternative tool to generate a time-frequency representation of a given time series. The performance of the CWT is proved to be more flexible than other usual approaches such as Short-Time Fourier Transform (STFT), where the size of the analysis window is restricted for all frequencies and the accuracy of solution is limited by the time-frequency resolution tradeoff. The superiority of the wavelets is more tangible in the case of non-stationary nature of the measurements and the existence of sudden changes in time direction [5,6].

In the case of STFT analysis [7], where the optimization of the window length is difficult for short or non-stationary time series, outputs are averaged over different states or conditions and short and non-stationary events blurred. On the other hand, the width of the window is changed in the case of CWT as the transform is computed for every single frequency component (scale). The frequency bands grow and shrink with the frequency (scale) being used. This allows good frequency resolution at low frequencies and good time resolution at high frequencies [8].

SVM CLASSIFICATION

The method of Support Vector Machine (SVM) is a supervised learning method, which can be used for classification based on the concept of feature space. Support Vector Machine algorithms have been used successfully for classification in numerous applications [9,10]. The training phase of SVM is used to construct a separating hyperplane with a maximum margin (Fig. 1) to distinguish between the different classes (system states). The decision function $D(x)$ generated by the SVM classifier is related with the distance from the separating hyperplane to classify the unknown data. Any unknown data point x with a feature vector is classified as either *Class 1* if $D(x) > 0$ or *Class 2* if $D(x) < 0$, [11].

The SVM-based algorithm is used to detect the system states (here: an undesired object is present or not). Due to the time delay between the feature vectors, a classifier [12] based on the SVM algorithm is developed for each individual acceleration signal.

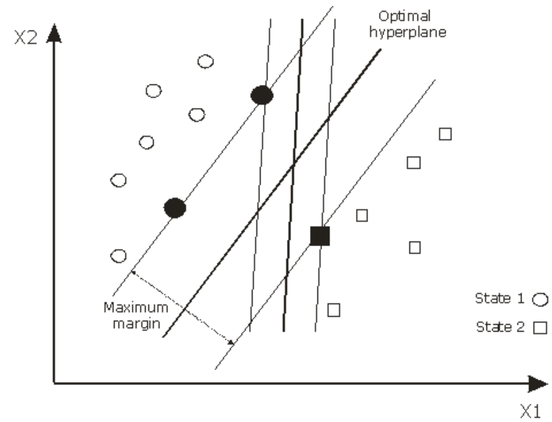


Figure 1. Support vector machine (Feature space).

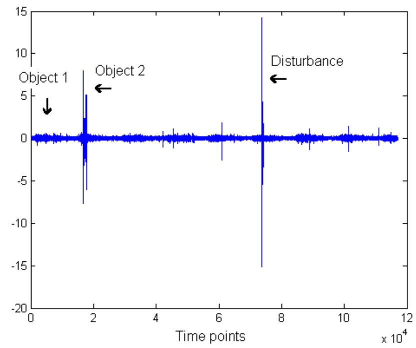
IMPLEMENTATION AND RESULTS

As an example of the sensor data, the time series signal in Fig. 2a represents the acceleration signal of sensor 1. To present the concept of solution and for the purpose of comparison [13], the signal is filtered using STFT (Fig. 2b) and CWT (Fig. 2c). The acceleration signal in Fig. 2a has two marked events (object exists) at time points about 8000 and 17000 which correspond to time points about 30 and 70 in the STFT (Fig. 2b) and time points about 8000 and 17000 in the CWT (Fig. 2c) respectively. A disturbing event (no object exists) can be recognized in Fig. 2a at time point about 74000.

The second object (time point about 17000) and the disturbing event (time point about 74000) are clearly recognized in the STFT and CWT results, however in the STFT result the two events look similar whereas in the CWT results they look different. In the case of CWT, the higher scales (low frequencies) in case of the second object are more strongly excited than the lower ones, while the lower scales (higher frequencies) in the case of the disturbing event are more strongly excited. The higher scales (lower frequencies) of the disturbance have lower energy than the lower ones (higher frequencies). This is an advantage of the CWT approach in this data set and could be a base rule for further filtering of the signals.

The first existing object in the sample data (time point about 8000) is not clearly recognized using the time series signal (Fig. 2a). In the STFT the excitation of the low frequencies gives indication about the existence of the object, whereas the existence of the object is more indicated in the CWT results due to a longer band of high scales (low frequencies). In Fig. 2d the first part of Fig. 2c containing the two existing objects in larger scale is presented.

The proposed CWT-based detection system algorithm with parallel classifiers is presented in Fig. 3. The system is composed of four parallel classifiers fused together to deliver more reliable decision about the existence of the object. The multiple stage individual classifiers include feature extraction, filtration and detection processes. The goal of the classifiers is to detect effects similar to those accompanied with the existence of the undesired objects to be detected, and to avoid disturbances having similar effects. Usually disturbances are mixed of different effects, therefore detecting effects known previously as non-object leads to negative decision for all the points



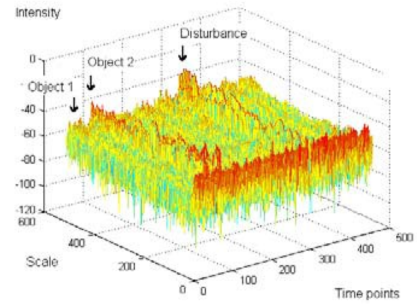
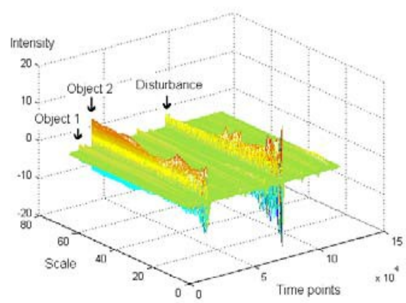


Figure 2a. Acceleration signal of sensor 1 Fig 2b: STFT decomposition of sensor signal 1.



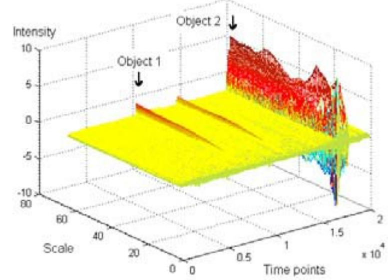


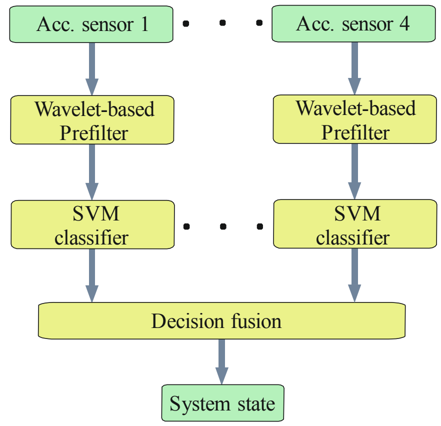
Figure 2c. CWT decomposition of the signal Fig 2d: First part of the CWT decomposition.

nearby, regardless of positive decisions of the first branch. The combined decisions help in reducing the rate of the false alarms.

The wavelet-based prefilters include the CWT filter and additional filter based on the previously mentioned distinction between the shape of the object effect and the disturbance effect in the results of the CWT filter.

The decision fusion module includes the combination of the individual decisions confirming existence or non-existence of the object to be detected, along with a fuzzy-based filter used for decision weights accumulation. The individual decision points are weighted according to the accumulated weights of the distance to the decision limit (Fig. 4). This process is performed in case of dissimilar delivered decisions from the individual classifiers about the system state and aims to avoid misclassification of system states as well as to meet a reliable decision about the presence of the undesired objects.

The CWT filter has the advantage of lower level of disturbance which assists further filtering of the CWT results. Indeed a considerable part of the non-object data in the CWT output can be offset by using simple thresholds. Proper selection of the CWT parameters (Haar wavelet) can lead to stronger distinction between the effect of the object and the effect of the non-object in the CWT output. On the other hand, this can also lead to neglecting the weak objects which could be even weaker.



Figur 3. The detection system.

The CWT output also has the advantage of different shapes of the disturbing events from the shape of the object effect. Additionally the mechanism of CWT transform gives better accuracy and resolution of the effect caused by the object which leads to long and uniform shape of the object to be detected.

The results of the CWT-based detection system are summarized in Table 1. The best individual accuracy of detection achieved is 60% (classifiers 1 and 2), which is accompanied with high rate of false alarms. It is necessary to mention that increasing the accuracy of the training of the individual classifiers will lead to improvements in the detection accuracy; however the rate of the false alarms would also be increased accordingly. During the development of the detection system, and according to the requirements of the mechanical system, a compromise between accuracy and rate of false alarms has to be achieved. Indeed this is considered one of the potential points to improve the system.

Based on individual and fused results of the system, it can be seen that fusing of the classifiers including detection of non-object effects leads to an improvement of the

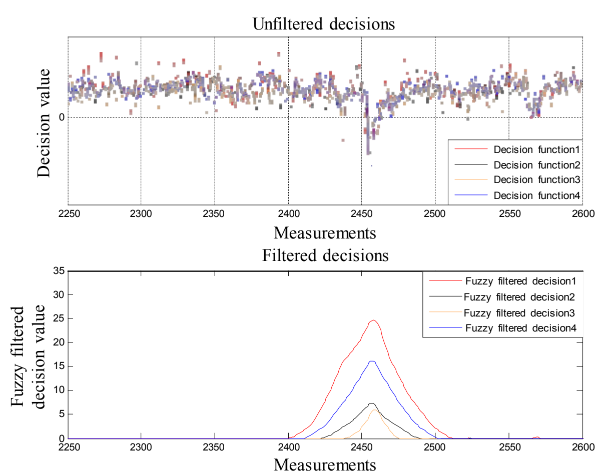


Figure 4. Unfiltered/filtered decision functions.

false alarm rate of the classifier (23 objects) and the rate of detection of the system (66%).

The improvement in the resulting accuracy indicates that the individual sensors (classifiers) have different views according to their mounted position as well as to the behavior of the transported materials including the undesired objects. This means that each individual classifier detects undesired objects possibly not detected by other classifiers. It is also necessary to recall that the false alarms in the individual sensors are not necessarily identical.

It is also necessary to mention that the accuracy of the system listed in Table 1 is not the targeted accuracy of the industrial process as it represents a module among other detection modules fused together and build the targeted detection system to serve the previously mentioned industrial process. Fusing of the modules of the targeted system leads to more accurate and reliable detection of the undesired objects.

Table 1. Results of the CWT-based system.

Sensor / classifier	1	2	3	4
Training data	2645 (16 objects)			
Kernel/ S.V.	Radial Basis Function (RBF) / 1197 S.V.			
Test data	3861033 (35 objects)			
Individual detected objects	21 (60%)	21 (60%)	20 (57%)	18 (51%)
Individual false alarms	7	13	14	8
Total detected objects	23 (66%)			
Total false alarm	5			

CONCLUSION

An approach for feature-based multisensor fusion to develop a monitoring and diagnosis system in an industrial process is presented. The application goal is to monitor a production process for online detection of the existence of an undesired object in the process, which is difficult to recognize based on the classical methods of sensor individual evaluations such as threshold values. The proposed system is based on Support Vector Machine (SVM). The method of Continuous Wavelet Transform (CWT) is used for feature extraction. The extracted features are undergone multistage filtering process delivering individual decisions merged to provide the final decision concerning the existence of an undesired object in the production process.

The results of the preliminary applications of the system show an improvement of the performance of the detection rate as well as a decreasing rate of the false alarms. Undesired objects are distinguished from the disturbing events in the CWT-based approach, whereas weak undesired objects could be even weaker and subjected to neglection.

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