A Fusion Toolbox for Sensor Data Fusion in Industrial Recycling

Björn Karlsson, Jan-Ove Järrhed, and Peter Wide, *Member, IEEE*

***Abstract*—Information from different sensors can be fused in various ways. It is often difficult to choose the most suitable method for solving a fusion problem. In a measurement situation, the measured signal is often corrupted by disturbances (noise, etc.). It is, therefore, meaningless to compare crisp values without the corresponding uncertainty intervals.**

This paper describes a toolbox including nine different fusing methods. All methods are applied on training data, and the most suitable method is then used for solving the real fusion problem. In the example, fusion is performed on data for classification in an industrial recycling operation. The data is from different vision systems and an eddy current system. The fusion methods included in the toolbox are fuzzy logic with triangular and Gaussian shaped membership functions, fuzzy measures with triangular and Gaussian shapes, Bayes' statistics, artificial neural networks, multivariate analysis (PCA), a knowledge-based system, and a neuro-fuzzy system.

***Index Terms*—AC motors, dc motors, fuzzy logic, fuzzy neural networks, neural networks, robot vision systems.**

I. Introduction

THIS paper describes the fusion process of measurement data in an automated disassembly system for electrical motors of about 1 kW. The approach consists of two main activities described below, namely functionality check and automated disassembly.

A. Functionality Check

When an electrical motor reaches the scrap dealer a classification, for either reuse or disassembly, has to be done. From the scrap dealer's point of view, it is impossible to have knowledge about all products reaching his plant. An advanced sensor and classification system is needed to guide the scrap dealer. Electric motors have a rather simple construction principle, but there is a vast variety of the design depending on brand name and field of application.

A test method is suggested [1] where different defects in the motor performance are identified. The results of the tests contribute decisions regarding the motor condition, e.g., whether it should be repaired/reused or if disassembly is appropriate (see Fig. 1). The proposed test method is performed during a start-up sequence without any motor load. During the test, relevant information is compiled, e.g., motor currents, voltages, vibration, and rotation speed. Using signal processing and pattern recognition techniques a classification of the motor status is possible.

The different types of possible motor failures can be divided into two types: mechanical and electrical. The mechanical faults can be caused by unbalanced and worn-out bearings, while the faults of electrical character are mainly different kinds of insulation damage. The insulation of the windings is often mechanically worn out and damaged due to movements in the stator windings.

B. Automated Disassembly

As seen in Fig. 1, the motors are first classified either to be repaired or to be disassembled for material recycling. In the later case, the electrical junction box is removed manually. Thereafter, two traces are cut through the motor house to enable separation of motor house and stator. Then the motors are put on a conveyor belt. An industrial robot pick the motors from the conveyor belt for automated disassembly (see Fig. 2).

When a motor crosses the light beam at the end of the conveyor belt, a vision camera snaps a image of the motor. From this image, information is extracted and compared to a database. The industrial robot gets fused information about the motor from the vision and database systems. It grips the motor, rotates the motor 90°, and moves the motor from the conveyor belt to the dismantling station.

In the dismantling station, the end-shields, rotor, and motor house are removed. The motor foot is clamped. A new image is snapped by the vision system, and a comparison is performed to the database. The fixing screws holding the end-shield on the rotor axes side are identified by the vision system and the database. The robot then removes these fixing screws. Then, the robot grips the rotor axis and pulls out the rotor and the end-shield. Then the dismantling station separates the stator from the rest of the motor.

The robot grips the stator and moves it to the cutting station where the stator is cut in two halves. Thereafter, the stator windings are removed in the following way: The robot moves the stator from the cutting station to the hydraulic tractive system. There, the stator windings are pulled out from the stator. The hydraulic tractive system clamps the stator, and four hydraulic arms grip the windings and pull them out of the stator.

The last part of the disassembly station is a test station. In the test station, an eddy current probe and a vision system check that all copper has been removed. First, a vision system checks if it

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B. Karlsson is with the Department of Physics and Measurement Technology, Linköping University, Linköping, Sweden. He is also with the Department of Technology and Science, Örebro University, Örebro, Sweden (e-mail: bnk@ifm.liu.se).

J.-O. Järrhed is with the Department of Physics and Measurement Technology, Linköping University, Linköping, Sweden.

P. Wide is with the Department of Technology and Science, Örebro University, Örebro, Sweden.

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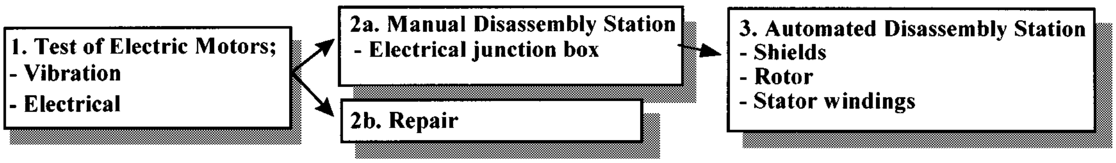

Fig. 1. Block diagram of the disassembly workstation.

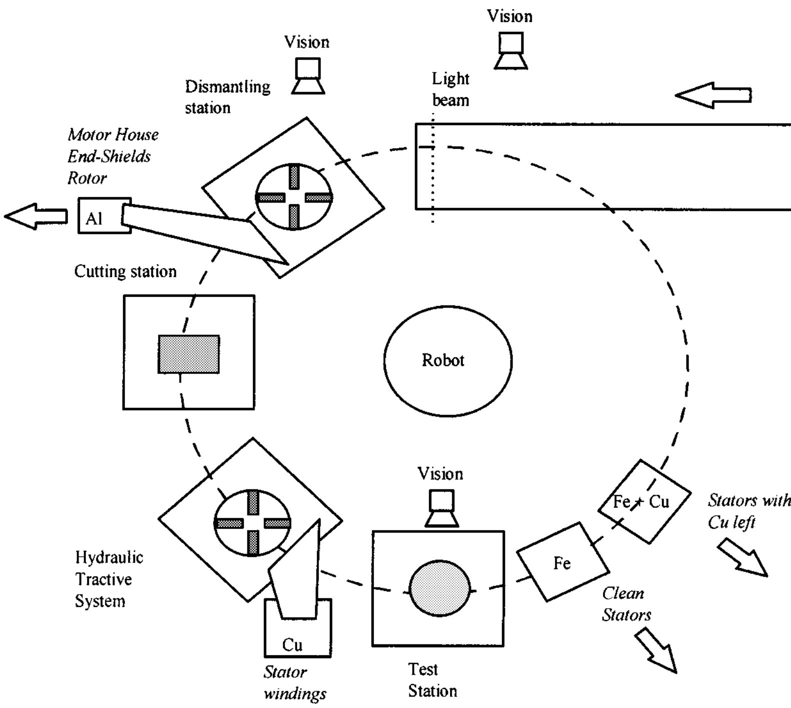

Fig. 2. Schematic layout of the disassembly station for electric motors.

could find any copper; then, an illuminating surface mounted under the stator is switched on. The vision system then counts the number of slots it is coming light through. Finally, the stator is put over an eddy current probe. The stator is then rotated around the probe who registers the materials in front of it. From the results of these tests, motors with some copper remaining are assigned for later manual removal of this copper, while the others are ready for recycling.

II. Sensor Toolbox

Suitable sensors measure the physical world. From the sensor data, different features are extracted. These features are then fused and classified by the different methods in the sensor toolbox. The developed sensor toolbox includes nine different methods for fusion and classification of data. The fusion methods included in the toolbox are fuzzy logic with triangular and Gaussian shaped membership functions, fuzzy measures with triangular and Gaussian shapes, Bayes' statistics, artificial neural networks, multivariate analysis (PCA), a knowledge based system, and a neuro-fuzzy system.

In the training phase, the fusion and classification are performed with all methods, Fig. 3.

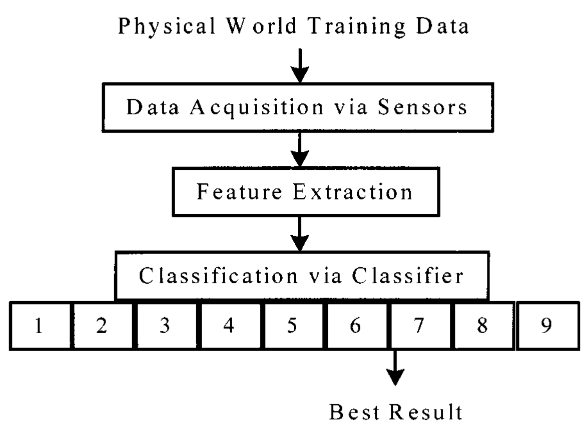

Fig. 3. Sensor fusion toolbox during the training phase, data acquisition via vision systems, and an eddy current system.

From the images, feature extractions of area (number of pixels), moment of inertia in the xx direction, in the yy direction and in the xy direction, rectangle big side, rectangle small side, and perimeter are done. These features are then sent to the classifier; the methods are

1) fuzzy logic with triangular shaped membership functions;
2) fuzzy logic with Gaussian shaped membership functions;
3) fuzzy measures with triangular shapes;
4) fuzzy measures with Gaussian shapes;
5) Bayes' statistics;
6) artificial neural networks;
7) multivariate analysis (PCA);

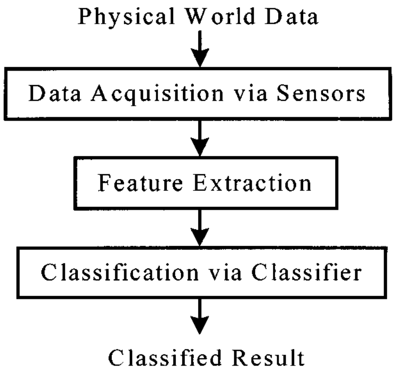

Fig. 4. Sensor fusion toolbox during the working phase.

8) a knowledge based system;
9) a neuro-fuzzy system.

When the training has been performed, an evaluation of the result is done, and the method with the best result is chosen as fusion and classification method for solving the problem (Fig. 4).

III. Different Fusion Methods

A short description of the different fusion methods used in the fusion toolbox follows below.

A. Fuzzy Methods

The fuzzy methods work with the following outputs. A feature is described by a fuzzy measure (FM) modeled in the range [0, 1] with an FM value $\mu = 1$ when there is total agreement with the model, $\mu = 0$ when there is no relevance to the model, and $\mu = 0.5$ for the condition with the highest degree of fuzziness between total agreement and total nonrelevance to the model.

1) Fuzzy Logic: Fuzzy logic is one of the possible fusion methods included in the toolbox. The information is classified by the intersection function

$$f_j = \bigcap_{i=1}^{N} \mu_{ij}(x_j) = \min[\mu_{1j}, \ldots, \mu_{Nj}] \tag{1}$$

where i is the feature and j is the model. The model with the largest f value is the winner. The membership functions are both of triangular and Gaussian shape.

2) Fuzzy Measures With Triangular Shapes: For each feature and each model, a triangular possibility measure $\mu_{Aj}(x)$, as given by (2), and shown in Fig. 5 is made forming a template for each model. Thus

$$\mu_{Aj}(x) = \begin{cases} 1 - \dfrac{|x - m_j|}{2\sigma_j} & |x - m_j| < 2\sigma_j \\ 0 & |x - m_j| \geq 2\sigma_j \end{cases} \tag{2}$$

where x is the quantity, m_j and σ_j are the mean value, and the standard deviation respectively.

When an incoming model should be classified, the different features are calculated and compared with the different templates, Fig. 6, giving FMs $\mu_1, \ldots, \mu_N$ for each template.

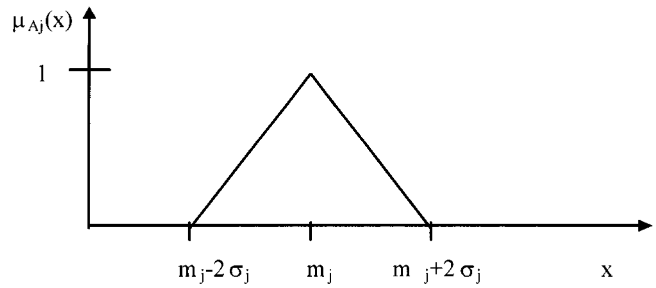

Fig. 5. Triangular possibility measure used to map uncertainty.

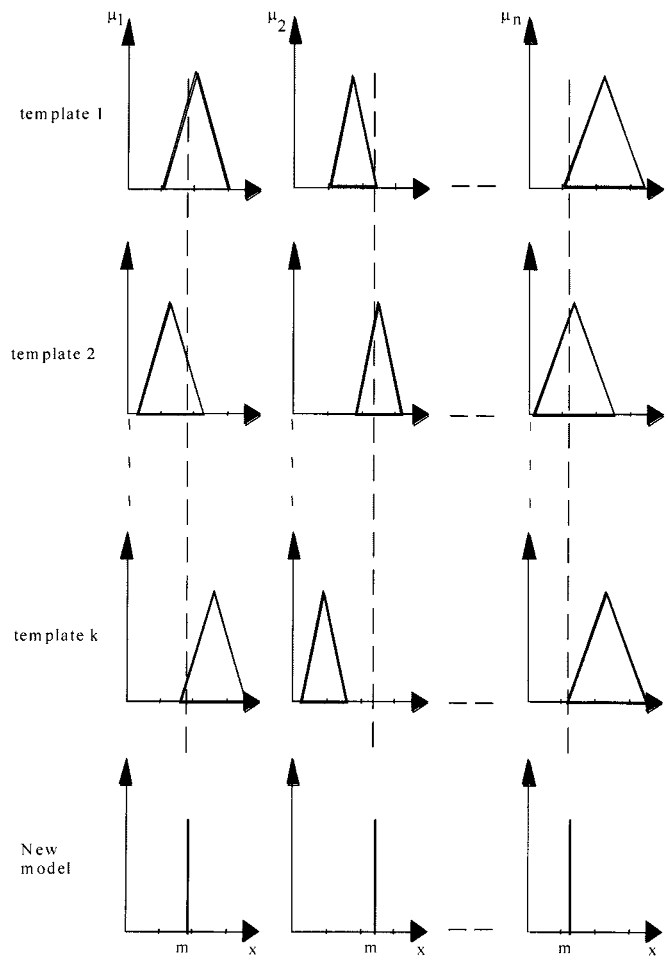

Fig. 6. Classification of a model by comparing with the templates.

The FMs for each template are then fused by algorithm (3) [2]

$$f(\mu_1, \ldots, \mu_N) = \left(\frac{1}{K^N - 1}\right) \cdot \left(\frac{-1 + K^N G_{\mu_1, \ldots, \mu_N}}{1 + G_{\mu_1, \ldots, \mu_N}}\right) \tag{3}$$

where G is given by (4)

$$G_{\mu_1, \ldots, \mu_N} = \prod_{i=1}^{N} \frac{1 + (K-1)\,\mu_i}{K - (K-1)\,\mu_i}; \qquad 1 < K < \infty \tag{4}$$

where the fuzzy measure μ_i describes the membership to a feature of a specific model, N is the number of features and K is a modifier. With a K value of one, (3) will become the common

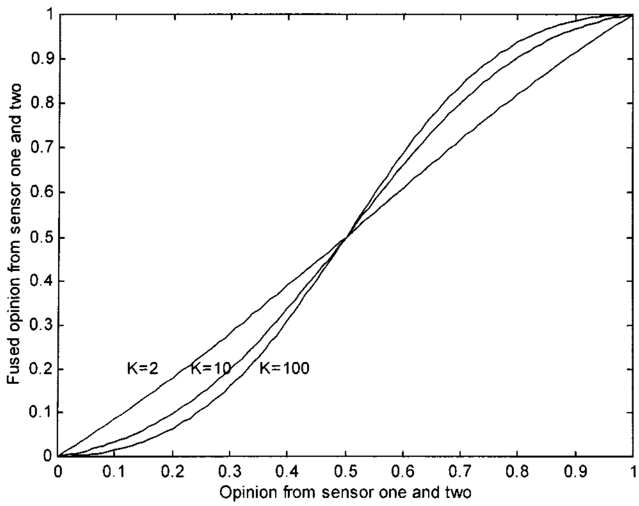

Fig. 7. Behavior of the function, f, for different K values, when fusing two sensors with the same opinion. The opinions are in the range [0, 1].

arithmetic mean and with a K value larger than one, fuzzy measures close to 0.5 will have smaller influence on the result than values closer to 0 and 1, Fig. 7.

3) Fuzzy Measures With Gaussian Shape: The fusion process is performed in the same way as above except that the possibility measures are Gaussian and given by (5)

$$\mu_{Aj}(x) = e^{-((x-m_j)^2/2\sigma_j^2)}. \tag{5}$$

B. Bayesian Statistics

In Bayesian statistics, the statistics of earlier measurements is used to classify a new measurement. The classification is performed by using Bayes' theorem (6) with Gaussian distribution [3]

$$P(C_k\,|x) = \frac{p(x\,|C_k)}{p(x)} \tag{6}$$

where $p(x|C_k)$ is the conditional probability density which specifies the probability that the observation is x, given that it belongs to class C_k and $p(x)$ is the probability density specifying the probability that the variable x is in a specified interval.

C. Artificial Neural Networks

For classification by artificial neural networks (ANNs) the radial basis function defined in (7) is used [4]

$$f_k(\mathbf{x}) = \sum_{l=1}^{M} w_{kl}\phi_l(\mathbf{x}) + w_{k0} \tag{7}$$

where $\boldsymbol{x}$ is the input vector, w_{kl} are the weights, w_{k0} is the bias, and ϕ_l is given by (8)

$$\phi_l(\mathbf{x}) = e^{-(|x-\mu_l|^2/2\sigma_l^2)} \tag{8}$$

where x is the quantity, μ_l and σ_l are the mean value, and the standard deviation, respectively.

D. Multivariate Analysis

As multivariable method, principal component analysis (PCA) [5] is used. PCA is a statistic mathematical method to transform (often strongly correlated) variables $X_1, \ldots, X_p$ to uncorrelated variables $Z_1, \ldots, Z_p$. The components $Z_1, \ldots, Z_p$ are a linear combination of $X_1, \ldots, X_p$ which are chosen such that: Z_1 is the component with the highest variance, Z_2 with the highest variance of the rest, and so on. The data is transformed to uncorrelated data with the total variance kept (9)

$$\begin{aligned} &Var[X_1] + Var[X_2] + \cdots + Var[X_p] \\ &\qquad = Var[Z_1] + Var[Z_2] + \cdots + Var[Z_p]. \end{aligned} \tag{9}$$

If the last $p-k$ values are small, they can be eliminated. To achieve a successful analysis, k should be much smaller than p. By this approximation method, a projection from p-dimensions to k-dimensions has been performed. This makes possible a regression analysis on the uncorrelated components $Z_1, \ldots, Z_k$, without any colinearity problems.

E. Knowledge-Based System

In the knowledge-based system, the classification is performed by dividing the measured data in intervals. To quantify these intervals, the mean value and the standard deviation are used. The method chooses the value one inside the interval and the value zero outside.

$$f(x) = \begin{cases} 1 & \text{if} \quad |x-m_j| < 2\sigma_j \\ 0 & \text{if} \quad |x-m_j| \geq 2\sigma_j. \end{cases}$$

The intersection operator then fuses the different intervals.

F. Neuro-Fuzzy System

ANNs have good abilities to classify, store, recall and associate information. By incorporating fuzzy principles into the ANN, a more flexible and robust system is obtained. In this work, a fuzzy classification with the back-propagation network [6] is performed. During the training sequence, one back-propagation network is built for each class. During the classification, the outputs from each network are then fused by (3) to a combined value. The network with the highest value given by (3) is then chosen as class in the classification, Fig. 8.

IV. Results

The toolbox has been used for classifying four different motor models in the range 0.075 kW to 0.18 kW. One image has been captured with the motor standing on its foot, Fig. 9, and another from the axis side of the motor, Fig. 10. Out of these images, 14 features of the motor have been taken using the vision program IMAQ for LabVIEW from National Instruments. The features from 15 images from different positions for each motor have been used. Of these images, 10 was used for training and the other five for validation.

For the fuzzy logic method with triangular shaped membership functions, the triangles were centered at the mean values of the training data, and the width of the triangles was two times the standard deviation. This method was only able to correctly

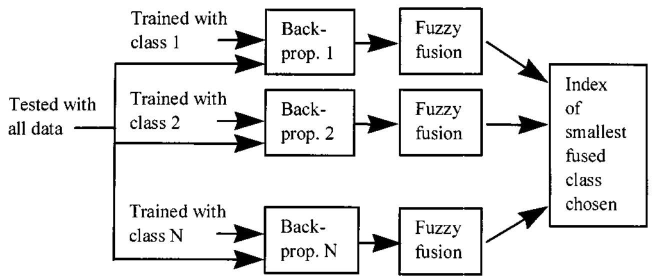

Fig. 8. Principles for neuro-fuzzy system for classification of data.

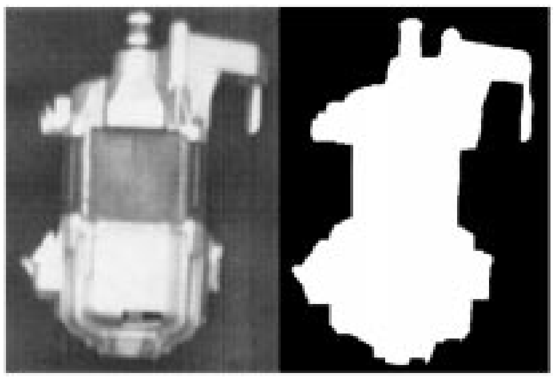

Fig. 9. Left: original image of the motor standing on its foot. Right: the image after image processing.

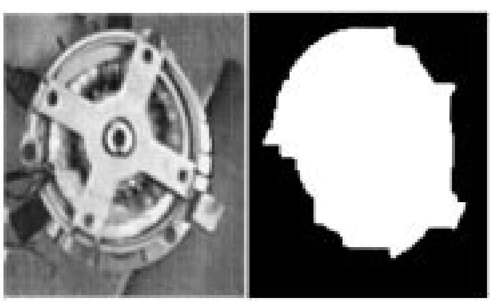

Fig. 10. Left: original image from the axis side of the motor. Right: processed image used for classification.

classify one of the 20 images. The other 19 images were classified as uncertain.

The fuzzy logic method with Gaussian shaped membership functions has the Gaussian centered at the mean value and the inflection point of the Gaussian at two times the standard deviation. This method was able to correctly classify 19 images. It failed to classify one image, which was classified as uncertain.

The fuzzy measurement methods, both with triangular and Gaussian shape, had the same membership functions as above, and these methods were able to classify all images to the correct class.

For the Bayesian methods the conditional probability and the probability density were calculated from the training data. This method classifies 19 images to the correct class and one to a wrong class.

The knowledge-based system was only able to classify one image to the correct class. The other 19 images were classified as uncertain.

When using the ANN approach, a radial basis network with a σ value equal to the mean value of the standard deviations of the different features was chosen. It gave a result of 16 correctly classified images and four wrongly classified images. However, if the σ value was enlarged to two times the standard deviation, all images were correctly classified.

In the PCA analysis, the three largest principal components were used for classification. Twelve images were correctly classified and eight were classified as uncertain. If the two largest components were used, the method was only able to classify two images to the correct class. With more than three components the classification result was sometimes better, but the result was very sensitive to noise.

For the neuro-fuzzy method, a back-propagation neural network with 14 neurons in the input layer, one hidden layer with five neurons, and one neuron in the output layer was built for each motor model, in this case four. During the validation, phase the image data was tested on the four networks, and the one giving the highest value given by (3) was chosen. For this method, 11 images were correctly classified, and nine were classified to the wrong class.

From the results of the test, it can be seen that fuzzy measures both with triangular and Gaussian shape and the radial basis ANN, with a standard deviation of two times the mean value of all standard deviations, were able to classify all images to the correct class. It is then, in this case, up to the operator to choose which method to use. In this case, it can be preferable to choose one of the fuzzy measurement methods because they are faster. The fuzzy measures can also be updated in a simple way by updating the mean value and the standard deviation after each classification. For the PCA and the neuro-fuzzy system, the low fit is a result of the small number of training data. With more training data, the result should have been better. For the knowledge-based system, the number of rules was too small. With more rules and more training data, the result of this method should have been better.

V. Conclusion

In this paper, nine different fusion methods have been used to classify data extracted from images taken of worn out industrial motors. We show that it is possible to correctly classify all images with three different methods: fuzzy measures with triangular shape, fuzzy measures with Gaussian shape, and a radial basis ANN. In other applications, other methods can be preferable.

This paper can be seen as the beginning of a fusion toolbox. In the future, the toolbox will have a larger set of different fusion methods, enabling for solving a wider range of problems. The fusion toolbox will hopefully be of value for the user, easing his task to select a suitable fusion tool.

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Björn Karlsson received the M.S. degree in physics from Linköping Institute of Technology, Linköping, Sweden, in 1996, and both the Lic. Eng. and Ph.D. degrees in measurement technology in 1998 and 1999, respectively.

He is now manager for the Optical Test Develpoment Group at Solectron, Sweden AB, Norrköping, Sweden. His research interest is in sensor fusion in multisensor systems for industrial applications.

Jan-Ove Järrhed, photograph and biography not available at the time of publication.

Peter Wide (M'92) was born in 1955 in Karlskoga, Sweden. He received the Dipl. Eng. and Licentiate of Technology degrees in measurement and physics from the University of Linköping, Linköping, Sweden, in 1984 and 1987, respectively. He received the Ph.D. degree from the University of Linköping in 1996 with the thesis entitled, "The human knowledge based sensor system—an integration between artificial intelligence and human experience."

Since 1999, he has been a Professor of measurement technology at Örebro University, Örebro, Sweden. He is also the Research Director of the Center for Applied Autonomous Sensor Systems, including four research laboratories: sensor and measurement, mobile robotics, intelligent control, and adaptive learning systems. His current research interests include sensors, feature extraction, artificial sensors, sensor data fusion, and quality measurements.