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QUALITY MONITORING IN MASS PRODUCTION OF MULTIAXIAL NON-CRIMP FABRICS BY USING A MULTISENSOR SYSTEM

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Abstract – Due to their excellent mechanical properties and light weight, fiber-reinforced plastic (FRP) has a huge potential as a way to reduce vehicle and airplane weight and is therefore a subject of interest for aerospace and automotive industries. To mass-produce FRP products, certain textile structures are commonly used as semifinished products, such as multiaxial non-crimp fabrics (NCF). Currently, there is no automated monitoring system capable of ensuring quality in NCF production. The purpose of this study is to develop tools and concepts that could lead to fully-automated quality control of non-crimp fabrics. Useful sensor concepts were developed based on a thorough requirement analysis. Sensor data fusion strategies were conceived and evaluated to combine image processing information and basis weight sensor information with the purpose of detecting relevant quality features in a textile sample. The developed algorithm was tested on a textile sample and a corresponding defect map was generated. Results showed that it is possible to identify common textile defect types by combining these two sensors.

Keywords: sensor data fusion, fiber-reinforced plastics, quality control, image processing, radiography

1. INTRODUCTION

Fiber-reinforced plastics (FRPs) have a large potential as a way to reduce vehicle and airplane weight. Therefore, FRPs, and especially carbon fiber-reinforced plastics (CFRPs), are subject of interest for aerospace industries, as well as for automotive industries and wind energy industries for its excellent mechanical properties and light weight [1].

Commonly, fiber textile products as multiaxial non-crimp fabrics (Figure 1, abbreviated: NCFs) are used as semifinished products for FRP. Multiaxial NCFs are textile structures with high mechanical properties, which generally consist of stretched and parallel layers of reinforcing fibers (rovings) or bands (fiber bundle). In order to combine these layers together, it is possible to utilize an additional material, such as mesh fiber. NCF production takes place on a warp knitting machine with multi-axial weft insertion, ensuring an economically advantageous industrialization of the manufacturing processes. Alongside the effective manufacturing, the main advantages of those textiles are high flexibility in terms of layer structure parameters (number of layers, fiber orientation, mass per unit area and fiber material) and textile parameters (bond type, seam length and thread inlet) [1].

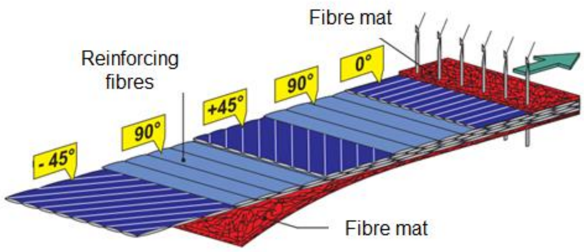

Figure 1. Manufacturing of multiaxial non-crimp fabrics.

Due to the heterogeneous and anisotropic nature of composite materials, the defects that can occur in CFRP components are different to those found in metals. Many defects occur at the interfaces between different layers, such as gas bubbles (porosities) between fiber and matrix, angular deviation of fibers (fiber misalignment), inclusions, voids, and thermal or shrinkage cracks. These defects can drastically alter local mechanical properties of components and can result in cracks, which can propagate to eventually lead to mechanical failure of the component. Thus, it is important to monitor the manufacturing process in order to detect such defects and discard flawed components [1, 2].

Even though the aforementioned production process can be applied to mass manufacturing, the high costs of production present an obstacle to the exploitation of the full potential. This is partly due to the fact that it is currently impossible to check product quality on the process line [3]. Indeed, there is no inline system able to perform continuous quality control of the process. The purpose of this study is to present concepts and tools for developing an automated quality monitoring system capable of supervising the production of NCFs.

2. STATE OF THE ART

2.1. Quality monitoring in CFRP production

The monitoring of production of multiaxial NCFs can be achieved by adopting non-destructive testing methods in the process line. Non-destructive testing methods (also called NDT methods) consist of a broad group of analysis techniques to estimate properties of materials, components or systems without permanently altering or damaging them. They are important in industry and science, as they can provide significant savings in time and money for quality testing [2].

Several methods are currently used for carbon-fiber composite inspection, such as ultrasonic testing, laser shearography, eddy current testing, thermography techniques, X-radiography, acoustic testing, white light interferometry, microwave, infrared and electron radiation. Each method can detect different material properties or defects and it is suitable for that specific task [2], [3]. The vast majority (95%) of non-destructive inspection tests in the production of fiber-reinforced composites are based on ultrasound [2], [4], [5], [6]. Indeed, these methods are suitable for detecting air voids, inclusions, delaminations, local resin inhomogeneities, fiber cracks and glue failures in components [2], [7]. However, ultrasound testing methods are suitable to inspect just finished products during late stage of production, since semi-finished products cannot be tested in wet conditions. On the other hand, air-coupled ultrasound inspection is not applicable to textile semi-finished products or textile fabrics because of sound attenuation through air gaps. Similarly, other methods based on different electromagnetic radiations (e.g. infrared or microwave) can be used to obtain the tomography of a work piece [8]. However, these methods present several problems when applied to CFRP products, as they feature a restricted measurement range, need extensive sample preparation or can damage the component. Image processing techniques are also used in micro-structural analysis through scanning electron microscopy (SEM), transmission electron microscopy (TEM) or atomic force microscopy (AFM) [6]. X-ray detectors can output received data to a computer, allowing online data processing. As composites materials are usually highly transparent to X-rays, it is appropriate to use low-energy X-rays in order not to get saturated images [2], [3]. X-ray computed tomography has a limited measurement range and its industrial development is prevented by high investment costs and security issues regarding protection from radiation [6], [9].

Thermography is a non-destructive testing method based on infrared radiation that can be used to detect inner defects of components [11], [13]. It can provide just blurred images of a reference surface with just few measuring points and for this reason it is suitable for qualitative analysis. As for ultrasound testing, thermography is applicable on finished products and not suitable for inspection during early stages of production, e.g. for monitoring non-crimp fabrics production.

A method based on a laser sensor and image processing is described in [10]. It can detect fiber orientation and inclusions which occur during the production of preforms. However, optical measurement systems are not able to get information regarding defects in inner layers, such as gas bubbles or fiber misalignment. Another example involving an optical system was developed by the company Profactor [14]. In this approach, an optical scanner performs eight image acquisitions under different lighting conditions and generates this way a picture of the structure. An image processing software highlights the presence of visible gas bubbles as well as angular deviations in the fiber orientation. However, this system has been never used for industrial applications, as satisfying results were reached just under laboratory conditions.

2.2. Multisensor data fusion for enhancing quality control

Multisensor data fusion is the process of combining data and related information from disparate sensors so that the achieved inferences are better than those which would be achieved by using the same sensors individually. Combining data from more sensors guarantees three main advantages over an analysis based on one sensor. An optimal combination of sensor data improves statistically the result by considering several independent observations. Establishing a relative motion among different sensors can lead to an improvement of the overall observation process. Finally, adopting sensors of different types enhances observability, as different physical features can be measured and combined. [15], [16]

Multisensor data fusion has gained a key role in production metrology. From the point of view of dimensional metrology, multisensor data fusion may be defined as "the process of combining data from several information sources (sensors) into a common representational format in order that the metrological evaluation can benefit from all available sensor information and data" [17]. In this perspective, the purpose of combining sensor data is to improve significantly quality and accuracy of measurements in a production process.

Regarding the lightweight industry, an important application developed at the Laboratory of is capable of performing inline inspection of textile structures [18]. This automated system carries out the placement and alignment of fiber-reinforced composite structures. It consists of an optical sensor which detects the local fiber orientation and of a light sections sensor that identifies the position of the contour of textile preforms. Whereas the optical sensor coarsely detects the contour of each layer, the light section source exploits this information to follow a scanning path. Subsequently, the light section sensor can provide more accurate measurements of the boundary. Finally, the joint information is used to determine position and alignment for each textile layer. This system is also used to control the 3D layer deformation that occurs in the drapery process.

Another machine vision application for large 3D carbon-fiber-reinforced structures was developed at the Laboratory for Machine Tools (WZL) of RWTH Aachen University, [19]. It combines light section sensors and image processing cameras with a robot system to perform quality control tasks. Data fusion occurs by integrating measuring information from these different sensors and thus reconstructing the 3D component geometry.

3. CONCEPTS AND METHODS

Even if the aforementioned sensors can efficiently perform specific tasks (i.e. to identify or quantify determined defect types), they are not able to conduct a complete inspection of multiaxial non-crimp fabrics. In order to assure quality in multiaxial NCF production, it is necessary to develop a quality control system which can combine information from different sensors into a joint representation. The process of sensor data fusion has the aim of overcoming the limits of the individual sensor and providing a defect map that shows the position and the extent of defects in the fabric. With this purpose, a multisensor system (Figure 2) which combines basis weight sensor and an optical camera was developed and tested.

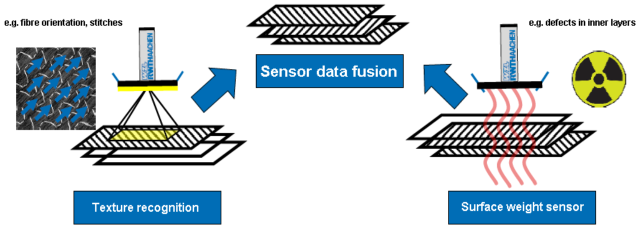

Figure 2. Sensor data fusion concept.

3.1. Basis weight sensor

Basis weight measurement methods show their potential in the detection of volumetric defects, such as voids, porosity or delamination. These are particularly relevant in increasingly thick or complex samples, such as multiaxial non-crimp fabrics. In this application, an X-ray sensor was used to assess the fabric basis weight. Radiographic inspection methods are suitable for high-speed production, as they can inspect products continuously. X-ray sensors consist of an X-ray source and a detector. X-rays travelling through the fabric material are attenuated according to the Lambert-Beer law

$$I = I_0 e^{-\mu d} \tag{1}$$

where I_0 represents the intensity of the emitted radiation, I is the intensity of transmitted radiation, μ is the linear attenuation coefficient and d is material thickness. In turn, the linear attenuation coefficient is defined as follows

$$\mu = \rho \cdot \sigma \tag{2}$$

being ρ the material density and σ the mass absorption coefficient, which depends on the radiation photon energy and the material. The basis weight of a carbon fabric can be expressed as follows

$$bw = \rho \cdot d \tag{3}$$

The detector provides a measure for the transmitted radiation intensity. By combining (1), (2) and (3), it possible to derive an expression for the fabric basis weight.

$$bw = \frac{1}{\sigma} ln \left(\frac{I}{I_0}\right) \tag{4}$$

The sensor used in this study is an X-ray sensor of the BST-ProControl (Figure 3).

Figure 3. X-ray sensor and equipment.

3.2. Optical sensor

Measuring the local orientation of fibers in the upper textile layer is fundamental for detecting defects in multiaxial NCF. This can occur using an image processing method [19]. To acquire good-quality images, a high-resolution camera and a dome illuminator (Figure 4) were used. This configuration ensures that a suitable contrast among textile elements, such as fibers and seams, is achieved. Subsequently, a reliable measure for the local fiber orientation can be achieved by assessing the local pixel orientation. The latter can be evaluated as suggested by Schmitt et al. [18], i.e. by considering the structure tensor of small image regions on the basis of the concept of eigenvector matrix.

Figure 4. Camera and dome.

In order to overcome the limits of the individual sensors, information from the optical sensor and from the X-ray sensor has to be combined into a joint representation. The purpose of the data fusion process design is to develop concepts and tools for an inspection system capable of analyzing each point (x,y) of a textile fabric and provide information about quality. Quality information for each point can be organized in a defect map useful to identify the location of defects on the fabric. In particular, the fusion process takes place combining the local value of the basis weight bw(x,y) to the detected local fiber orientation θ(x,y). This involves data preprocessing to associate univocally every value of bw(x,y) to the corresponding value of θ(x,y). As different sensors may have different resolutions, it is necessary to adapt the data resolution in such a way that the two different datasets share the same resolution. This can occur by reducing the highest dataset resolution. In addition, the reference systems of the two datasets have to be made coincident, so that they share the same origin and orientation.

Afterwards, the reference values $((\overline{bw}), \overline{\theta})$ representing the reference quantities which are theoretically achieved for a defect-free textile are considered. $\overline{\theta}$ represents namely the desired fiber orientation, whereas $(\overline{bw})$ is the mean basis weight related to N desired layers. For each textile point, local deviations of the basis weight bw(x,y) and of the fiber orientation θ(x,y) should be evaluated to form the following database:

$$\begin{cases} \Delta\theta(x,y) = \theta(x,y) - \bar{\theta} \\ \Delta bw(x,y) = bw(x,y) - \overline{bw} \end{cases} \tag{5}$$

In order to improve the algorithm generality, data have to be scaled so that values lie in the range [-1, +1] by dividing the deviations by their maximum value detected on the sample textile. This is also useful for algorithms which perform dot product, such as support vector machines. The achieved representation is the following

$$\begin{cases} \Delta^*\theta(x,y) = \frac{\Delta\theta(x,y)}{\max(|\Delta\theta(x,y)|)} \\ \Delta^* bw(x,y) = \frac{\Delta bw(x,y)}{\max(|\Delta bw(x,y)|)} \end{cases} \tag{6}$$

Finally, a process of class assignment occurs. Training data are associated with a priori information about their quality which is useful to develop a heuristic algorithm. A binary variable is associated with a couple $(\Delta^*\theta, \Delta^* bw)$ and represents whether the considered point respects certain quality requirements or not. The overall preprocessing that precedes classification is represented in Figure 5.

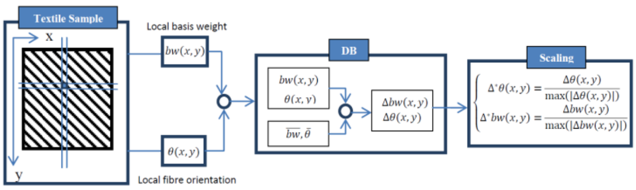

Figure 5. Signal preprocessing.

Once the preprocessing has completed, it is possible to proceed with the sensor data fusion. The fusion process can be realized by using a classification method, such as a support vector machine [20], [21]. The problem of designing a suitable support vector machine which performs correctly classification tasks consists of finding the weights α_i, the bias b, the box constraint C, the slack variables ξ_i and the kernel function K that solve the support vector problem

$$\min_{\underline{w},b,\xi} \ \frac{1}{2}\underline{w}^T\underline{w} + C\sum_{i=1}^{l}\xi_i \tag{7}$$

$$\text{such that: } \begin{cases} y_i\left(\underline{w}^T\phi(\underline{x}_i) + b\right) \geq 1 - \xi_i \\ \xi_i \geq 0 \end{cases}, \forall i = 1, \ldots, l \tag{8}$$

$$\text{being: } b = \sum \alpha_i y_i x_i \text{ and } K(\underline{x}_i, \underline{x}_j) = \phi^T(\underline{x}_i)\phi(\underline{x}_j) \tag{9}$$

These parameters define the best separating hyperplane which divides the two classes of data. The hyperplane is identified by defining its support vectors. As regards the requirements for this algorithm, it is supposed to perform a non-linear classification. A radial basis function (RBF) has been firstly used as kernel function:

$$K(\underline{x}_i, \underline{x}_j) = e^{-\gamma\|\underline{x}_i - \underline{x}_j\|^2}, \ \gamma > 0 \tag{10}$$

In particular, a Gaussian RBF has been used by imposing $\gamma = \frac{1}{2\sigma_{rbf}^2}$.

In conclusion, the algorithm for quality inspection consists of a stage of data preprocessing, followed by a process of data classification. This checks the following condition

$$\sum \alpha_i K(\underline{s}_i, \underline{x}) + b \geq 0 \tag{11}$$

where $\underline{s}_i$ are the support vectors. If this condition holds, the textile point (x,y) meets the quality requirements, otherwise it is considered as defective. The overall process is represented in Figure 6.

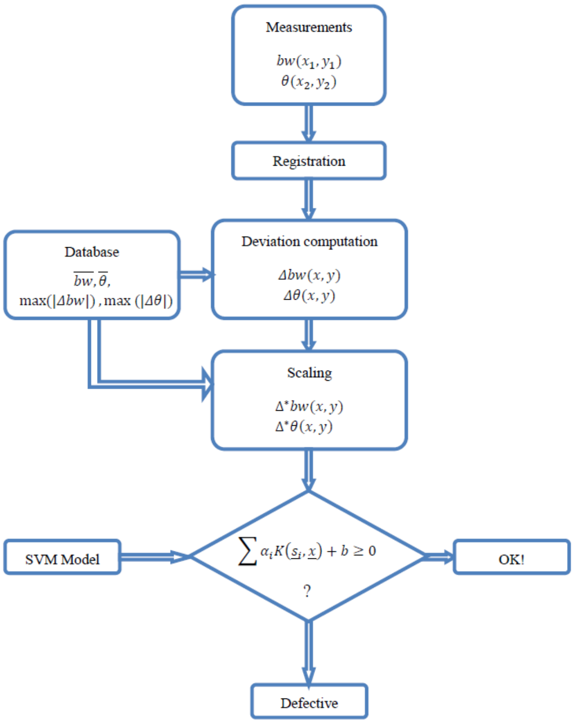

Figure 1. Quality inspection algorithm.

4. RESULTS

In order to perform the data fusion process and develop suitable rules and algorithms, it is necessary to have a training dataset of values (θ(x,y), bw(x,y)) for a finite region of the same textile sample. The latter was analyzed by both the camera and the X-ray sensor. As regards the basis weight measurement, the transmitted radiation reaches the ionization chamber of the detector and generated a voltage proportional to the detected intensity. The basis weight deviation has the following expression

$$\Delta bw = -\frac{1}{\sigma}\left(\ln\left(\frac{U}{U_0}\right) - \ln\left(\frac{\bar{U}}{U_0}\right)\right) = -\frac{1}{\sigma}\ln\left(\frac{U}{\bar{U}}\right) \tag{12}$$

where U represents the detector voltage, U_0 the reference voltage and $\bar{U}$ is the voltage referred to the nominal basis weight. The maximum absolute deviation is therefore

$$\max(\Delta bw) = \frac{1}{\sigma}\max\left(\left|ln\left(\frac{U}{\bar{U}}\right)\right|\right) = \frac{1}{\sigma}\left|\ln\left(\frac{Um}{\bar{U}}\right)\right| \tag{13}$$

The expression of the scaled basis weight deviation can be derived as follows

$$\Delta^* bw = \frac{-(\ln(U) - \ln(\bar{U}))}{|\ln(Um) - \ln(\bar{U})|} \tag{14}$$

which does not depend on the mass absorption coefficient. Therefore, the basis weight input depends only on the detected voltage, on the reference voltage and on the voltage which determines the maximum absolute deviation. It is also possible to use the scaled voltage deviation as data fusion input

$$\Delta^{*}U = \frac{U-\bar{U}}{|U_m - \bar{U}|} \tag{15}$$

Measurements were performed in 9 different points of the textile sample (see Figure 7), as the X-ray measuring system is not equipped with an actuating device. Point 3 is located in a region where several rovings are missing. Points 1, 5 and 9 are located where only few fibers are missing. Points 2, 3, 6, 4 and 8 are located where no textile defect has been identified.

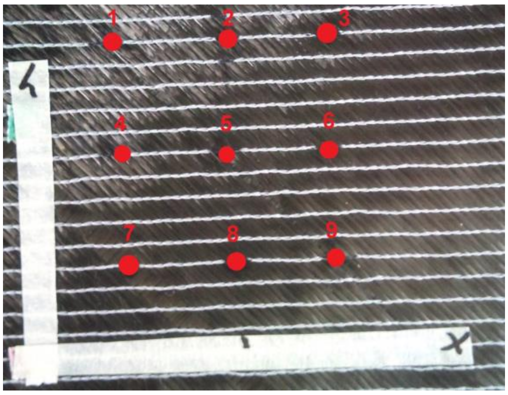

Figure 7. Textile sample showing measurement points.

For each point a voltage value was measured. Noteworthy is that the voltage measured in 1, 5, 9 is significantly lower than that of point 3. The reason is that the focus spot diameter is larger than the defect width and therefore the defect-free region have been measured, as well. This voltage is approximately an average value between the values measured in the defect-free region and the one measured in point 3.

In order to obtain a voltage matrix U(x,y) for each point of the considered region, it is necessary to generate randomly values by using the measured values as mean values and the corresponding standard deviation as variability range. The random generation process has a uniform distribution. This trick coarsely simulates the variability which occurs in the measurement process.

Subsequently, a MATLAB program was developed to compute the unknown support vector machine parameters. As the chosen kernel is a Gaussian radial basis function, the identification of a suitable separating hyperplane can be carried out by finding optimal values for the box constraint C and the RBF constant, σ_{rbf}. Whereas C influences the quantity of support vectors, σ_{rbf} defines the shape of the hyperplane. The optimization process was performed varying those parameters exponentially by using the powers of two and checking whether the hyperplane that these parameters delimit well the two classes.

The achieved hyperplane as well as a graphical representation of the two distinct sensor matrices is shown in Figure 8. Values which meet quality requirements are represented with green points, whereas values indicated as flawed are shown with red dots.

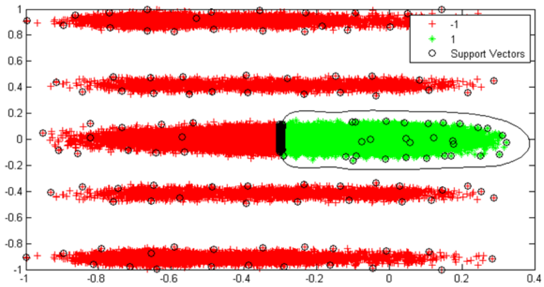

Figure 8.Scaled deviation map: defective points (red dots) and defect-free points (green dots).

After the classification process occurred, it is possible to represent the class of each point on a binary map, using the support vector machine previously developed to classify scaled data and provide a graphical representation of the textile fabric. In particular, defect-free data are represented with color green, whereas flawed points are represented with color red. Figure 9 represents the defect map of the textile sample used for training the support vector machine.

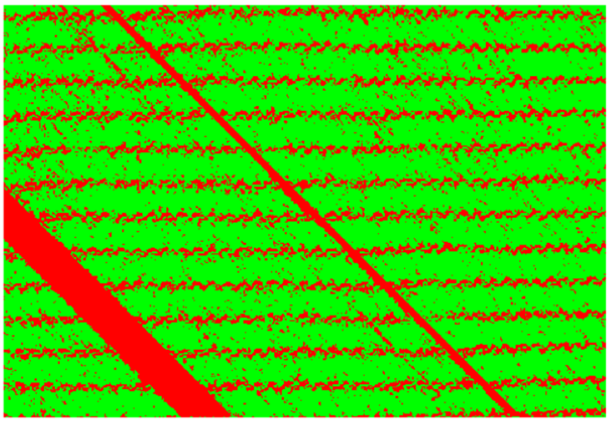

Figure 9. Defect map of a textile sample.

In the defect map it is possible to identify macroscopic defects (missing rovings) as well as seams and smaller defects, such as regions with low density of fibers or where undulation phenomena occur. Seams are indicated as defects, as well. It is however possible to apply filters which can systematically remove seams from a defect map.

To show the potential of sensor data fusion, it has also been created a fictitious textile sample which is identical to previous one except for the fact the large defect (many missing rovings, lower-left zone of Figure 9) has been placed in an inner layer in place of the upper layer. Therefore, it cannot be detected by the optical sensor. Scaled data regarding fiber orientation and detector voltage are represented together with the related defect map in Figure 10.

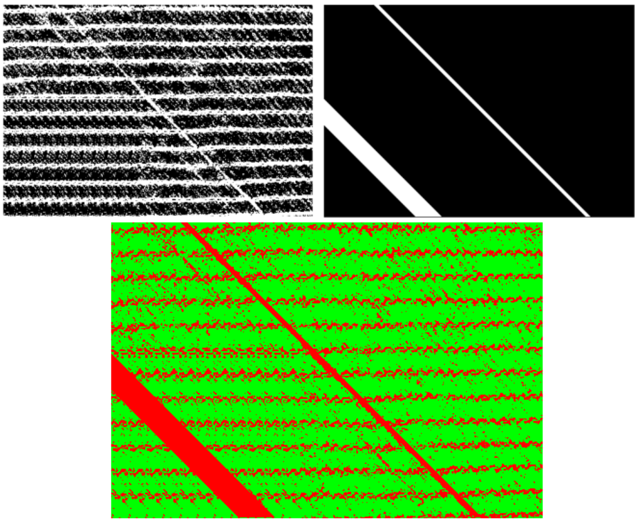

Figure 10. Fiber orientation deviation map (top left), basis weight deviation map (top right), overall defect map (bottom).

5. CONCLUSIONS

In conclusion, sensor data fusion concepts were developed in order to perform quality inspection of multiaxial non-crimp fabrics. The algorithm is based on a support vector machine and combines information from a basis weight sensor and a texture recognition camera. A defect map based on this algorithm was generated for a textile sample and an example of how the potential of sensor data fusion may be exploited with respect to the use of individual sensors has been illustrated.

Support vector machines therefore represent a valid candidate for the quality inspection of multiaxial fabrics, as they showed a high degree of both accuracy and robustness. In order to implement the algorithm into the production line and thus automate the quality monitoring, image processing algorithms and in particular pattern recognition techniques can be used to process the defect map and recognize automatically defects, while simultaneously filtering seams. Doing so, it is possible to assess automatically defect position, type and severity.

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