

## 금속 벨로우즈 용접의 결점 탐지를 위한 서포터 벡터 머신의 이용

박민철\*, 변영태\*, 김동원\*\*

# Use of Support Vector Machines for Defect Detection of Metal Bellows Welding

Min-Chul Park \*, Young-Tae Byun \*, Dong-Won Kim \*\*

### 요 약

기존 벨로우즈의 용접 불량은 현미경을 이용한 작업자의 수작업과 육안확인으로 진행되고 있어 효율과 능률면에 서 많은 부작용이 있다. 본 논문에서 이러한 문제점을 해결하고자 서포트 벡터 머신을 이용한다. 제안된 시스템은 서포트 벡터 머신을 이용하여 작업자의 경험적인 방법을 대체하고, 이미지 처리 과정에서 작업자로부터 발생하는 불규칙성을 극복할 수 있다. 또한 현미경과 3D 디스플레이 시스템을 통하여 제품불량을 쉽게 확인할 수 있다. 자동 화 측정 장치로부터 얻어진 실험결과를 통하여 용접불량은 허용되는 에러 범위 아래로 개선됐음을 알 수 있다.

▶ Keywords : 금속 벨로우즈 용접, 서포터 벡터 머신, 결점탐지.

### Abstract

Typically welded bellows are checked with human eye and microscope, and then go through leakage test of gas. The proposed system alternates these heuristic techniques using support vector machines. Image procedures in the proposed method can cover the irregularity problem induced from human being. To get easy observation through microscope, 3D display system is also exploited. Experimental results from this automatic measurement show the welding detection is done within one tenth of permitted error range.

▶ Keywords : Metal Bellows Welding, Support Vector Machines, Defect Detection.

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\* 한국과학기술원 센서시스템연구센터 (Sensor System Research Center, KIST)

\*\* 인하공업전문대학 디지털전자과(Dept. of Digital Electronics, Inha Technical College)

## I. Introduction

Industrial welded metal bellows are in shape of flexible pipeline. Generally bellows and related products which bellows applied are used to controls the flow of various types of fluids. The most common form of the bellows is as pairs of washer-shaped discs of thin sheet metal stamped from strip stock that normally ranges in thickness from 0.025 to 0.254mm. Welding operation has to be done with very accurate and detailed operation because this pipeline will control the flow of high temperature and high pressure fluids or gas.

To secure the safety standards defect detection from welding is very important. Typically welded bellows are checked by human being with microscope, and then go through leakage test of gas. The proposed system alternates this typical procedure by human being of the welded bellows with automatic system using support vector machines (SVM). The SVM is introduced by Vapnik [1] and it is an elegant tool for solving pattern recognition and regression problems. Over the past few years, a lot of researchers from neural network and mathematical programming fields are attracted to devote themselves to the research on SVM. The basic theory is well understood and applications work successfully in practice. In many applications [2-4], SVM has been shown to provide higher performance than traditional learning machines [5] and has been introduced as powerful tools. In this paper, SVM and kernel methods (KMs) are first applied to identify metal bellows welding.

Because the defect detection procedures by human being are based on the proficiency, checking the welding sequence is irregular and hard to maintain high qualities. Therefore mass production is difficult and unit cost is also expensive. Consequently, monitoring bellows welding and full automatic machine system for defect are needed. For monitoring and observing metal bellows welding

through microscope easily and conveniently, 3D display system [11] is exploited in this paper also. Typical observation procedure looking through microscope is done by human being for a fairly long time. The visual fatigue is another interesting problem to solve. Regarding this problem, our 3D display can alleviate this problem using camera, microscope, and vision system. In this paper a method of defect detection by 3D display and image processing is proposed. 3D display is used for the workers to observe the bellows instead of looking through microscope. Image processing is performed for automatic measurement. Experimental results show that automatic welding detection is done within one tenth of permitted error range.

## II. Metal Bellows Welding and its Defect detection system

The definition of metal bellows from Wikipedia is as follows [6]. Metal bellows are elastic vessels that can be compressed when pressure is applied to the outside of the vessel, or extended under vacuum. When the pressure or vacuum is released, the bellows will return to its original shape. Bellows technology of the 20th and 21st century is centered on metal bellows. These high-technology products bear little resemblance to the original leather bellows used traditionally in fireplaces and forges. Figs. 1-2 show the examples of metal bellows and its welding sequence. As stated before, the welding should be done with very precisely and carefully. If a defective weld is discovered after a structure has been completed, the weld may have to be removed and the entire welding job must be done over again. Therefore improperly executed welding can cause much cost of repairs and rework time.



Fig. 1. Metal bellows

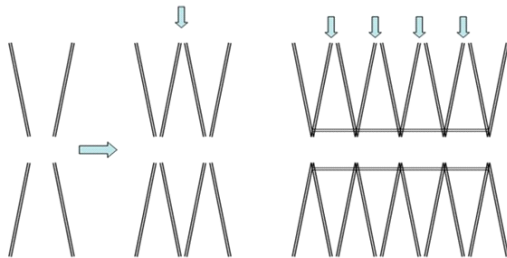


Fig. 2. Welding sequence

To ensure weld quality, samples from every batch are thoroughly inspected. Generally welded bellows inspection is done under human eye and microscopic examination as shown in Fig. 3. Unfortunately, this kind of manual inspection is needed much of time, effort and worker's attention. Convenient and high performance based automatic inspection system is necessary. Our automatic inspection system is composed of two parts which are 3D display and image processing. 3D display is for the workers to examine easily the bellows instead of microscope and image processing is for automatic inspection, respectively.



Fig. 3 Metal bellows welding operation by human being with microscope.

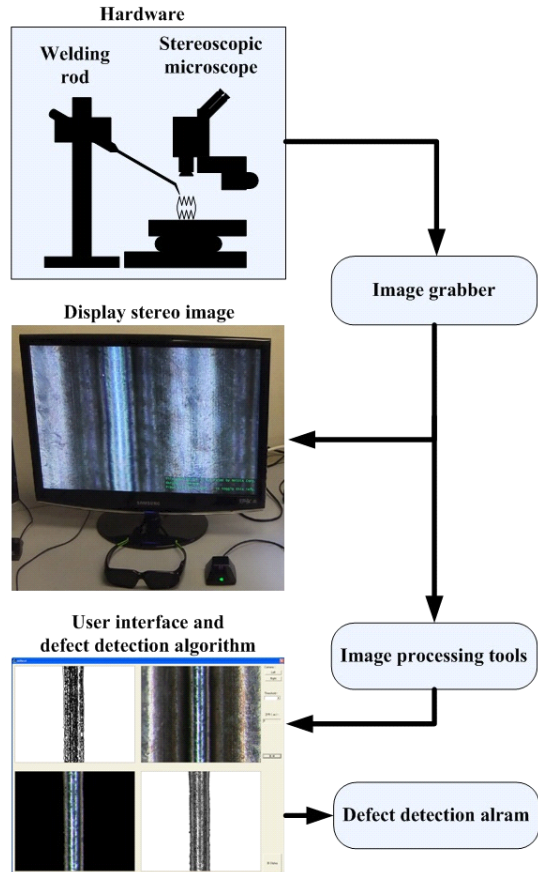


Fig. 4 Automatic inspection system

The automatic inspection system has three parts. One is an optical stereomicroscope with two CCD cameras mounted on the top of the microscope. Using this stereomicroscope, left and right images can be acquired simultaneously. Another is the welding rod and welding machine to weld the bellows. And the other is a PC with 3D display and shutter glasses. Fig. 4 shows the automatic inspection system. Regarding defect detection algorithm for welding lines of the bellows, image processing is consisted of two main parts: The region of interest (ROI) extraction and extraction of welding lines of the bellows, respectively. To get easy understanding for the normal and defected welding lines, these two examples are shown in Figs. 5-6.

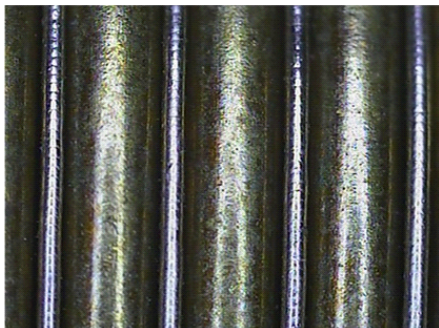


Fig. 5 Normal welding lines

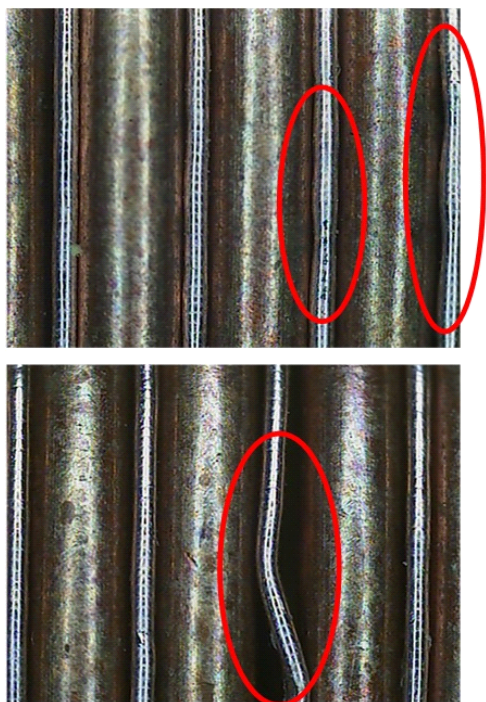


Fig. 6 Defected welding lines

### 1. Extraction of region of interest (ROI)

To recognize welding lines of the bellows, extracting the ROI from the acquired image is indispensable. This process consists of multiple morphological operations and labeling stage. Morphological operations are used to understand the structure or form of an image. This usually means identifying objects or boundaries within an image. Morphological operations play a key role in

applications such as machine vision and automatic object detection. The most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image.

Connected components labeling scans an image and groups, and pixels into components based on pixel connectivity, i.e. all pixels in a connected component share similar pixel intensity values and are in some way connected with each other. Once all groups have been determined, each pixel is labeled with a graylevel or a color (color labeling) according to the component that it was assigned to. Extracting and labeling of various disjoint and connected components in an image is central to many automated image analysis applications.

Fig. 7 depicts how the ROI can be extracted from the input image. The input image is binarized with a threshold value then multiple erosions and dilation are applied to the image. Also edge image is calculated and stored. According to the threshold value, defect detection rate is varied. After multiple morphological operations are applied, each welding line becomes a group of black pixels as shown in Fig. 7. Then the labeling is applied to the image. Thus, the image contains several labeled regions that include welding line. Finally, the edge image is used to extract outline of welding lines in the labeled regions.

### 2. Extraction of feature of a welding line

To extract a feature of a welding line, derivation value and average value from the extracted outline of the welding lines from the bellows are calculated. The derivation value and the average value are

calculated from each outline of the welding lines. Extracted the derivation values and the average values are shown in Fig. 8. Since outline of the defected welding lines is more rough than normal welding line, derivation values of normal welding lines are placed low area of the graph and derivation values of defected welding lines are positioned high area of the graph. Figure 9 shows our threshold values. A threshold is applied to define defected welding line and the threshold is defined heuristic approach to increase detect deflection rate.

Figure 10 shows extracted feature values in our bellows welding line image database. By using this feature, we can detect defected welding line and bellows. Figs. 11-12 show the examples of welding lines after image processing procedures.

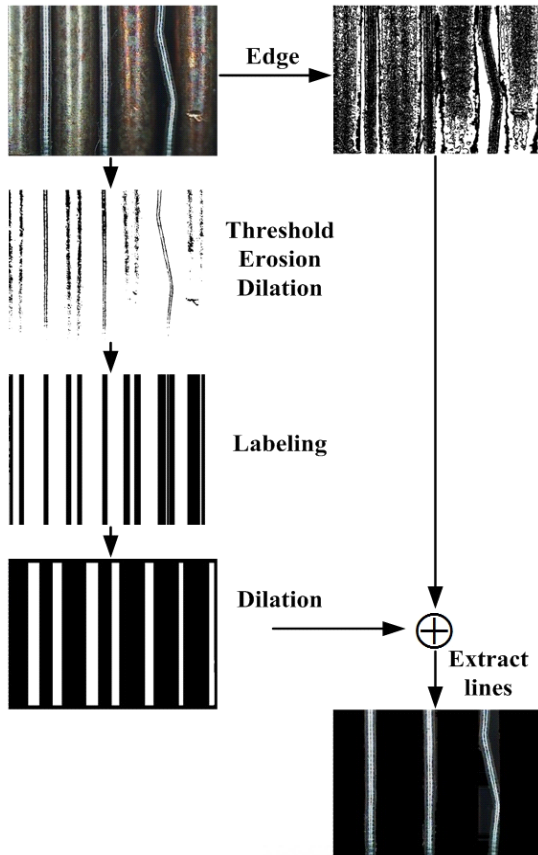


Fig. 7 Extracting ROI from acquired image

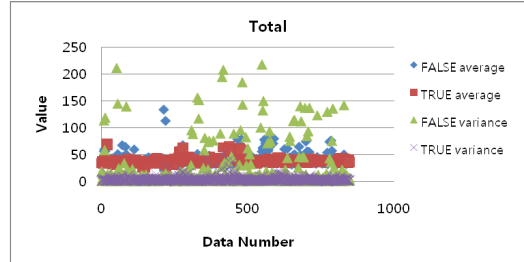


Fig. 8 Extracted derivation values

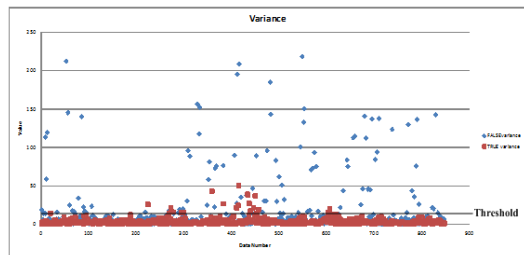


Fig. 9 Threshold values

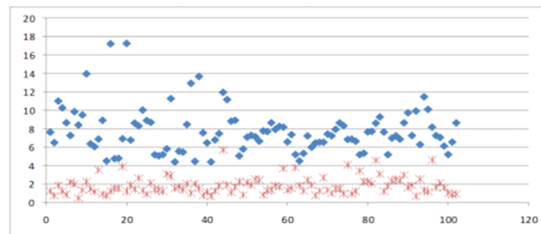


Fig. 10 Feature data for SVM learning

Calculation of the derivation and average values are done using following equations, respectively.

$$W = \text{width},$$

$$\bar{X} = \frac{1}{W} \sum_{y=0}^W X, \quad \text{Var}(X) = \frac{1}{W} \sum_{y=0}^W (X - \bar{X})^2,$$

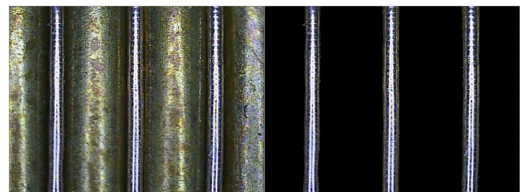


Fig. 11 Example of normal welding lines after image processing

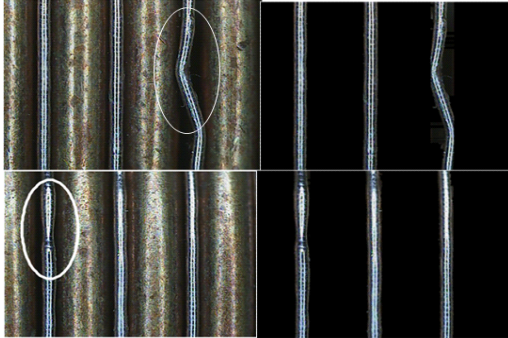


Fig. 12 Example of defected welding lines after image processing

### 3. Support Vector Machines (SVM)

Using the extracted feature values(data) from Figs. 8-10, SVM is learned and trained for defect detection. In the database, defected welding lines and normal welding lines are included. Support vector machines (SVM) is well known classifier. The fundamental idea of SVM is to construct a hyperplane as the decision line, which separates the positive (+1) classes from the negative (-1) ones with the largest margin. The other property of SVM is that it can use diverse kernels in dealing with the input vectors. The standard kernels are linear, polynomial, Gaussian and sigmoid kernels. Between the standard kernel functions, linear kernel is applied for the defect detection of metal bellows welding. This section presents some basic concepts of the support vector machines (SVM). A more detailed explanation can be found in [7-10].

Let  $(\mathbf{x}^k, y_k)$ ,  $k=1, \dots, m$  represent the training examples for the classification problem: each vector  $\mathbf{x}^k \in R^n$  belongs to the class  $y_k \in \{-1, +1\}$ . Assuming linearly separable classes, there exists a separating hyperplane such that

$$y_k(\mathbf{w}^T \mathbf{x}^k + b) > 0, \quad k=1, \dots, m. \quad (1)$$

The distance between the separating hyperplane and the closest data points is the margin of

separation. The goal of an SVM is to maximize this margin. One may rescale the weights  $\mathbf{w}$  and the bias  $b$  so that the constraints (1) can be rewritten as

$$y_k(\mathbf{w}^T \mathbf{x}^k + b) \geq 1, \quad k=1, \dots, m. \quad (2)$$

As a consequence, the margin of separation is  $\frac{1}{\|\mathbf{w}\|}$  and the maximization of the margin is equivalent to the minimization of the Euclidean norm of the weight vector. The corresponding weights and bias represent the separating optimal hyperplane. The data point  $\mathbf{x}^k$  for which the constraints (2) are satisfied with the equality sign are called support vectors. Introducing the Lagrange multipliers  $\alpha_1, \dots, \alpha_m$ , the minimization of  $\|\mathbf{w}\|^2$  under constraints (2) can be recast in the following dual form:

Find the minimum of

$$J(\mathbf{a}) = -\sum_{k=1}^m \alpha_k + \frac{1}{2} \sum_{k=1}^m \sum_{j=1}^m \alpha_k \alpha_j y_k y_j (\mathbf{x}^k)^T \mathbf{x}^j \quad (3)$$

subject to the linear constraints

$$\sum_{k=1}^m \alpha_k y_k = 0, \quad (4)$$

$$\alpha_k \geq 0, \quad k=1, \dots, m \quad (5)$$

By solving this QP problem, one obtains the optimum Lagrange multipliers  $\alpha_k$ , one for each data point. Using these Lagrange multipliers the optimum weight vector may be determined as

$$\mathbf{w} = \sum_{k=1}^m \alpha_k y_k \mathbf{x}^k \quad (6)$$

Only the Lagrange multipliers corresponding to the support vectors are greater than zero:

consequently the optimum weights depend uniquely on the support vectors (SVs). For an SV  $\mathbf{x}^i$ , it is  $\mathbf{w}^T \mathbf{x}^i + b = y_i$

The optimum bias can be computed using this. In practice, it is better to average the values obtained by considering the set of all support vectors, according to

$$b = \frac{1}{\#SV} \sum_{i \in SV} \left( y_i - \sum_{k=1}^m \alpha_k y_k (\mathbf{x}^k)^T \mathbf{x}^i \right) \quad (7)$$

In which the expression (6) has been used.

The SVM formulation can be extended to the case of non-separable classes. By introducing the slack variables  $\xi_k$  the optimal class separation can be obtained from

$$\min \frac{1}{2} \mathbf{w}^T \mathbf{w} + C \sum_{k=1}^m \xi_k \quad (8)$$

$$\begin{aligned} \text{s.t. } & y_k (\mathbf{w}^T \mathbf{x}^k + b) \geq 1 - \xi_k \\ & \xi_k \geq 0, \\ & k = 1, \dots, m \end{aligned} \quad (9)$$

In this case, the margin of separation is said to be *soft*. The constant  $C > 0$  is user-defined and controls the tradeoff between maximization of the margin and minimization of classification errors on the training data set. The dual formulation of the QP is the same as (3)-(4) with the only difference is in the bound constraints, which now become:

$$0 \leq \alpha_k \leq C, \quad k = 1, \dots, m \quad (10)$$

In this case, for the optimum Lagrange multipliers we have:  $0 < \alpha_k < C$  for support vector;  $\alpha_k = 0$  for points correctly classified with  $\xi_k = 0$ ;

and  $\alpha_k = C$  for points with  $\xi_k > 0$ . In the soft margin case the relation (7) still holds, but the average is taken over all  $\mathbf{x}^i$  such that  $\alpha_i > 0$ .

Finally the threshold  $b$  may be chosen a priori: in this case, the SVM can be trained by finding the minimum of

$$J(\boldsymbol{\alpha}) = - \sum_{k=1}^m (1-b) \alpha_k + \frac{1}{2} \sum_{k=1}^m \sum_{j=1}^m \alpha_k \alpha_j y_k y_j (\mathbf{x}^k)^T \mathbf{x}^j \quad (11)$$

subject to the bound constraints  $0 \leq \alpha_k \leq C, \quad k = 1, \dots, m$

With respect to the general formulation, the equality constraint (4) disappears and it is easier to find the solution. From the optimum Lagrange multipliers, one obtains the weight vector using (6)

Regarding parameters used in the SVM [10], we summarized several options and their values as shown in Table 1.

Table 1. Parameters and their values in SVM

OPTIONS	VALUES	
General	Verbosity output	
Learning	Classification	Epsilon width: 0.1
		Unbiased hyperplane
Performance estimation	Leave-one-out estimate	Rho : 1.0
		Depth : 0
Optimization	QP-subproblem	Max. size : 10
	Termination criterion	Epsilon: 0.001

### III. Experiments and Performance Analysis

Using this proposed automatic inspection system, experiment is performed and its performance is analyzed. Fig. 13 shows proposed and realized

automatic defect inspection system. Stereo images are captured using Matrox Morphis board from the microscope. Two CMOS image sensors are installed on the ocular lens part and microscope Nikon SMZ800 is used. 3D display gives a stereoscopic perception of 3D depth to the user. The basic requirement is to present offset images that are displayed separately to the left and right eye. Both images are combined in the brain to give the perception of 3D depth. Recently, two type of 3D display is being sold such as LCD shuttering method and polarization methods. In the proposed system, LCD shuttering method is used because of observing the object with more high resolution. To realize 3D display by shuttering method Samsung SyncMaster 2233RZ, Geforce 3D vision kit and NVIDIA GeForce GTS 250 graphic card are used.

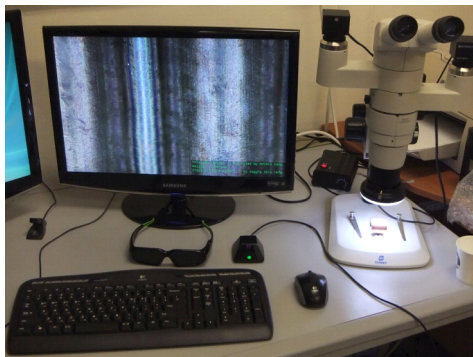


Fig. 13 Realized automatic inspection system for metal bellows welding

Figs. 14 and 15 show the detected welding points and its precisely segmented welding region, respectively. Enclosed by green box in Fig. 14 indicates electrode tip is welded with a constant interval. Fig. 15 shows the inspected defect system with 3D display. By analyzing changes of edges and slant of segmented region welding defects are well inspected.

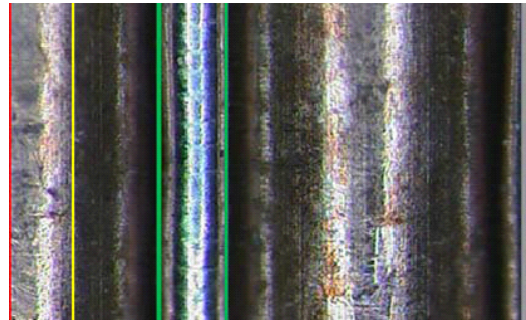


Fig. 14. Detected welding points

We construct a bellows welding line image database to evaluate the performance of the proposed system. All images in the present database are acquired from the stereoscopic microscope described in previous section, and the database contains 1381 magnified metal bellows welding images. Table 2 summarizes the results for defect detection rate. It shows that the SVM shows better result than the threshold method.

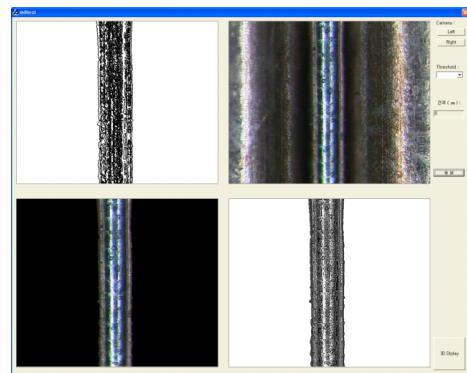


Fig. 15. Precisely segmented welding region

Table 2. Comparison of Detection Rates

Method		Recognition Rate (%)	No. of Data
Human-operated detection		77.84	3033
SVM	corrected set	94.69	2872
	Incorrected set	5.31	161

## IV. Conclusions

In this paper automatic defect inspection system using support vector machines (SVM) with 3D display and image processing for the metal bellows welding is proposed. Generally, welded bellows are checked by human being with microscope, and then go through leakage test of gas. But the defect detection procedures by human being are based on the proficiency, checking the welding sequence is irregular and hard to maintain high qualities. Therefore mass production is difficult and unit cost is also expensive. To handle the defective from human being, automatic machine systems using SVM are depicted. For the visual fatigue problem the 3D display system with camera, microscope and vision system is exploited. For automatic measurement and the extraction of region of interest, and feature values from the image, image processing is performed. Finally, for the defect detection SVM is applied and the overall recognition rates are generally good. Experimental results show that automatic welding detection is done within acceptable error range. This would be the first case to make use of 3D display, image processing, and SVM usage in industrial manufacturing system.

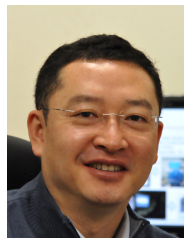
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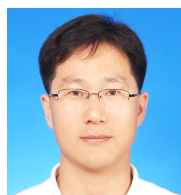
## 저 자 소 개



**박 민 철**  
1994: 홍익대학교 전자공학과 공학사.  
1997: 동경대학교  
전자정보공학과 공학석사.  
2000: 동경대학교  
전자정보공학과 공학박사  
현 재: 한국과학기술연구원  
센서시스템연구센터, 책임연구원  
관심분야: 3차원 정보처리  
Email : minchul@kist.re.kr



**변 영 태**  
1985: 고려대학교 물리학과 이학사.  
1989: 고려대학교  
물리학과 이학석사.  
1995: 고려대학교  
물리학과 이학박사  
현 재: 한국과학기술연구원  
센서시스템연구센터, 책임연구원  
관심분야: 나노센서, 센서플랫폼,  
U-Healthcare, 의료기기  
Email : byt427@kist.re.kr



**김 동 원**  
2007: 고려대학교  
전기공학과 공학박사 .  
2008: UC Berkeley(Prof. Zadeh그룹)  
EECS Post-Doc.  
2009: UC Davis, AME Post-Doc.  
현 재: 인하공업전문대학  
디지털전자과 교수  
관심분야: 제어시스템, 로보틱스,  
지능연산  
Email : dwnkim@inhac.ac.kr