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Optimizing Machine Vision System Setup Accuracy by Six-Sigma DMAIC Approach

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***Abstract*—**Machine vision system provides automatic inspection to reduce manufacturing costs considerably. However, only a few principles have been found to optimize machine vision system and help it function more accurately in industrial practice. Mostly, there were complicated and impractical design techniques to improve the accuracy of machine vision system. This paper discusses implementing the Six Sigma Define, Measure, Analyze, Improve, and Control (DMAIC) approach to optimize the setup parameters of machine vision system when it is used as a direct measurement technique. This research follows a case study showing how Six Sigma DMAIC methodology has been put into use.

***Keywords*—**DMAIC, machine vision system, process capability, Taguchi parameter design.

I. Introduction

MACHINE vision system plays an important role in modern industrial practice for two reasons. The first one is the short analysis speed (cycle time) of the manufacturing process, which makes it easier to meet customers' requirements [1]. Another one is on-line measurement. With the growing demand for industrial automation in manufacturing, on-line measurement contributes to overcoming subjectivity, fatigue, slowness, and cost associated with human inspection in the manufacturing environment [2].

The two advantages mentioned above imply that machine vision is versatile enough to inspect different parts. Actually, machine vision system has been widely used in manufacturing for the past decades. According to Jones [3] and Kumar et al. [1], machine vision system has two main application areas in industry: automatic inspection and robot guidance. Of these two main application areas, automatic inspection is the most important [3]. Derganc et al. [4] describe a machine vision system for inspecting bearings. Dhanasekar and Ramamoorthy [5] attempt to evaluate the surface roughness of uniformly moving machined surfaces using machine vision technique. With the development of the manufacturing system, automatic inspection is considered to be in more details. It includes not only inspection tasks by the inspector, but also a measurement of dimensions, counting, bar-code reading and so on [3]. In the classification of automatic inspection, dimension measurement is the most important application because it plays a vital role in improving products' quality, which is the key element to satisfying customer demands in the modern industrial and manufacturing field [6]. Sun et al. [7] use machine vision system to inspect the electric contact defects through measuring its dimensions.

Regardless of its importance in quality control management, a constraint to the accuracy of machine vision system caused it to develop slowly throughout the past 10 years [8]. Pfeifer and Wiegers [9] present the image optimization method to handle the adjustment of illumination parameters. The method presented focuses on 2D-inspection tasks using machine vision with incident illumination directly onto reflective metal surfaces. Although this method addresses the inaccuracy issue when machine vision system is used as tool wear monitoring, it is not useful when machine vision system acts as a direct measurement technique. In their study, Golnabi and Asadpour [10] present that one of the most important design parameters in developing a machine vision system is the optimal type of lighting, such as fiber optics, tungsten lamps, fluorescent, and light - emitting diodes. Nevertheless, changing light source is not a proper approach when a machine vision system acts as on-line inspection. There are not many solutions for how to handle the problem of optimizing the accuracy of machine vision system in past research. According to the study of Lahajnar et al. [11], the most important optimizing issues of a machine vision technique system are hardware and software setup. Even though each machine vision system has its own standard setup parameters, they are not exactly fixed. To some extent, they depend on the environment and measurement parts. Due to the possible optimizing setup parameters relying on the users' setup procedure, Seulin et al. [12] use numerous attempts on lighting features and relative positions between the camera, the lighting, and the object. Because it is not systematic, this trial and error method is complicated and difficult to implement. In order to overcome these drawbacks, this research focused on the implementation of Six Sigma DMAIC, which is a systematic methodology, to reduce variances of dimension measurements resulting from different setup parameters of machine vision system.

II. Application of Six Sigma DMAIC Approach and Taguchi Method

This section explains methodologies to be adopted in this study. Fig. 1 illustrates the activities of DMAIC (Define opportunities, Measure performance, Analyze potential causes, Improve performance, and Control performance) approach in Six Sigma. DMAIC is the five-step approach that makes up the Six Sigma toolkit, and its sole objective is to drive costly variation away from manufacturing and business processes. Six Sigma is a continuous improvement process,

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focusing on the customer requirements, process alignment, and analytical rigor [13]. In many cases, root causes are difficult to find. Systematic implementation of DMAIC makes sure that the root causes of defects are found and then eliminated by concentrating on the outputs that customers need, so DMAIC becomes one of the most important quality methodologies. Thus, this research has implemented DMAIC based on the Six Sigma approach in order to optimize the accuracy of machine vision system.

Fig. 1 Steps and emphasis on DMAIC methodology

The DMAIC approach is widely used in recent research. Yeh et al. [14] use DMAIC to construct the evaluation framework for assessing the performance of supply chain management. Rohini et al. [15] propose the DMAIC Six Sigma approach to improving the process in the Operation Theatre of a corporate multi-specialty hospital. Since the DMAIC approach is adopted as a systematic method in many researches, it is used in this study. In the improve phase of DMAIC, the Taguchi method is an important methodology in design of experiment. It is defined as a set of measures called signal-to-noise (S/N) ratios that combine the mean and standard deviation into one measure in analyzing data from a robust design [16]. The complete procedure of the Taguchi design method can be divided into system design, parameter design, and tolerance design [17]. The steps in the Taguchi method's parameter design are selecting the proper orthogonal array (OA) according to the numbers of controllable factors (parameters), running experiments based on the OA, analyzing data, identifying the optimum condition, and conducting confirmation runs with the optimal levels of all the parameters [18].

Even though the Six Sigma DMAIC approach and Taguchi method were widely and systematically used in previous researches, they have not been adopted to optimize setup parameters of machine vision system. Currently, the methods of optimizing the setup parameters of machine vision system are mainly the physics/mechanical method and optimizing images now [10]. It would be more organized and systematic to use the Six Sigma DMAIC and Taguchi methodologies to optimize the setup parameters of machine vision system.

III. Case Study

This case study describes a systematic way of evaluating and optimizing machine vision system. Fig. 2 presents the machine vision system used in this study. It mainly consists of a camera, monitor, red light emitter, power supply, and target. With this equipment, the operator can easily measure a part by just pressing one button. However, machine vision setup is an important process that could lead to inaccurate dimension outputs. In this case, a three-person team was formed, consisting of individuals who had a good understanding of the Six Sigma concept, and a shared understanding of the problem and the project. The three-person team attempted to optimize machine vision setup parameters since it is one of the most important issues impacting the accuracy of machine vision. The first phase for the team was to define what was important in the machine vision system. Secondly, they measured the machine's current condition in measure phase. And thirdly, they analyzed the problem in analysis phase. The fourth phase was to improve by developing solutions, and the last phase was to control the performance. The scope of the study starts with defining opportunities.

Fig. 2 Machine vision system setup

A. DMAIC Phase 1 – Define Opportunities

Define opportunities is the first of five phases in the Six Sigma improvement process. In this phase, the team laid the foundation for the improvement effort the business is now pursuing. History has shown that a well-defined project with appropriate scope and objectives is a critical factor in the success of any improvement effort. A key output of this phase is determining the main issues of machine vision system that cause customers' dissatisfaction. In this phase, the most important objective is to identify customer needs. Critical to Quality (CTQ) conveys the quality of a product of service derived from the voice of the customer. In industrial practice, according to a machine vision system's usage in quality control management and the difficulty of improving the accuracy of its program, its setup parameters greatly affect the dimension accuracy. Therefore, the Critical to Quality characteristic of interest for this study was the difference between the parts' known dimensions and the measurements from machine vision system. This study considered that the dimensions from a CMM are true dimensions of parts. It aims at minimizing the difference between machine vision and CMM dimensions.

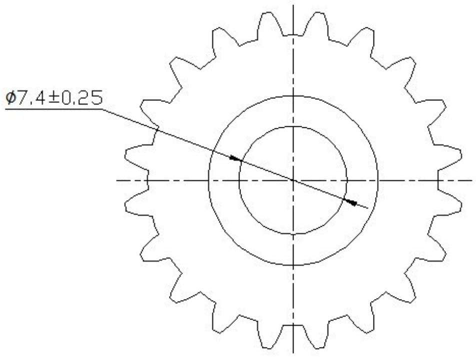


Fig. 3 Dimension of the gears in the experiment

In order to figure out the current accuracy of machine vision system, the project measured seven different gears' inner diameters in the same size. The gear used in the project is shown in Fig. 3. The true inner diameter dimensions of the seven gears were replaced by the dimensions from CMM. This study used the Six Sigma DMAIC approach to reduce the dimension variance that occurs from machine vision and CMM. Accuracy is used to denote the difference. The accuracy (denoted as y_{ijk}) of machine vision system is defined in (1):

$$y_{ijk} = x_{cmmj} - x_{ijk} \tag{1}$$

y_{ijk} - Accuracy; x_{cmmj} - Measurement from CMM as control dimensions, in millimeter; x_{ijk} - Measurement from machine vision system, in millimeter; i - Experimental runs; j - Part's number; k - Number of operator.

In the present problem, the dimension of the gear is shown in Fig. 3. Changing the parameters setting to reduce the variance between the dimensions from the CMM and machine vision system optimizes the accuracy of machine vision. In this phase, three team members were responsible for collecting data, starting from A Gauge Repeatability and Reproducibility (GRR), which are used to measure the current accuracy of machine vision system. A GRR study is normally used to validate and justify a capable measurement system. The measurement system is acceptable when the variability due to the measurement system is between 10% and 30% [19]. Based on the characteristics of the GRR study, the current condition of machine vision system was analyzed. Three operators and seven parts were involved in the study. A total of 63 observations on accuracy were collected for this study. The accuracy of the 63 observations and the analysis results from the GRR study are shown in Tables I and II, respectively.

TABLE I
OBSERVATION DATA OF ACCURACY (IN MM)

Operator1			Operator2			Operator3		
1	2	3	1	2	3	1	2	3
-0.081	-0.094	-0.088	-0.007	0.109	-0.019	-0.057	-0.047	-0.047
0.006	0.017	0.027	-0.002	-0.015	-0.071	-0.052	-0.066	-0.044
-0.054	-0.094	-0.099	-0.100	-0.054	-0.101	-0.015	-0.011	0.004
-0.074	0.032	-0.086	-0.041	0.115	0.146	-0.08	-0.062	-0.051
-0.017	-0.029	-0.019	-0.098	-0.071	-0.087	-0.026	-0.071	0.087
-0.058	-0.089	-0.059	0.086	-0.005	-0.068	0.057	0.062	0.042
-0.023	-0.032	0.029	-0.024	-0.09	-0.062	-0.058	-0.083	-0.088

TABLE II
RESULTS OF GRR STUDY

Equipment Variation	Appraiser Variation	R & R	%EV	%AV	%R&R
0.348	0.077	0.357	69.62%	15.50%	71.32%

During this stage, various process parameters were measured quantitatively and qualitatively. The Equipment Variation percentage (%EV) is up to 69.62%; however, the Appraiser Variation percentage (%AV) equals 15.5%. A big gap of %EV and %AV indicates that most of the error comes from the equipment variance. The high number of %EV contributes to a high %R&R, which equals 71.32%. It means that the measurement system is currently unacceptable. Moreover, the results from GRR file emphasize that the equipment setup from machine vision system is the source of inaccuracy. The analysis in define phase proves that extra setup procedures are needed in the current machine vision system.

B. DMAIC Phase 2 – Measure Performance

Measure Performance is the second phase of the Six Sigma Improvement Process, which builds on the outputs of the Define Opportunities phase. In this phase, the process Critical Customer Requirements (CCRs) are formalized with operational definitions to ensure the proper parameters are being measured from a variety of perspectives in order to determine how well the process is performing and what is happening inside the process to make it perform the way it is.

In this phase, the team identified the measures needed to evaluate how the process under review was performing. These measures directed the data collection that provided the team with actual performance data on the process.

Supplier-Input-Process-Output-Customer (SIPOC) provides process mapping that is extremely helpful in identifying processes that require improvement. The team developed an SIPOC chart, which presents a clear picture of setup process and analyzes main issues related to customers' requirements. Based on the SIPOC chart, basic setup steps are summarized.

Step1. Setup hardware: Hardware setup includes setup monitor, setup camera, setup remote, and setup power supply.

Step2. Setup software: Software setup includes setup camera register, setup image, registration, setup measurement.

Step3. Setup background: Background setup includes choose background color, place part in the right place.

Step4. Get results: Set calibration, read results.

After knowing the setup process and identifying the customer's requirements, the next step is to identify failure modes and measure the influence of controllable process parameters. The most appropriate tool in this stage is Failure Mode and Effects Analysis (FMEA). FMEA is a systematic tool for identifying effects or consequences of a potential product or process failure, ranking failures and developing methods to eliminate the chance of a failure occurring. After these potential reasons were discovered, their effects on the quality function were tested.

FMEA table in Fig. 4 shows the top five ranked potential failure modes. They are incorrect amount of lighting, vibration, incorrect height, incorrect color, and incorrect scaling input. FMEA is completed in the Measure phase of DMAIC and can provide recommended actions to minimize risks to the customer. In the next phase, the effects of potential failure modes were tested, and the proper solutions were determined.

Process Step/Input	Potential Failure Mode	Potential Failure Effects	SEV	Potential Causes	OCC	Current Controls	DET	RPN	Total RPN
Setup Environment	Incorrect amount of lighting	Inaccurate dimension reading	8	Poor surrounding environment	9	Visual	7	504	504
	Vibration	Inaccurate dimension reading	8		9		7	504	504
Setup Camera	Incorrect height	Inaccurate dimension reading	8	Lack of training	7	Visual	8	448	840
		Incorrect resolution of picture	7	Bad quality of camera	7		8	392	
Place Background	Incorrect color	Camera cannot recognize the shape/part	7	Lack of training	4	Visual	6	168	360
		Inaccurate dimension reading	8	Lack of correct background resource	4		6	192	
Set Calibration	Input incorrect dimension for scaling	Inaccurate dimension reading	8	Lack of training Inaccurate caliper reading	7	Caliper is used	7	392	392

Fig. 4 FMEA with top five potential failure modes

C. DMAIC Phase 3 – Analysis Opportunity

In this section, Analysis Opportunity, the project applied a fishbone diagram, a hypothesis for analyzing data and drawing data-based conclusions about why the process is performing as it is. These findings may lead the team toward additional data collection or allow the team to jump into the root cause analysis tools that play such an important role in effective problem solving. The outputs of this section were verified root causes that were eventually reduced or eliminated by the team's solutions. In the analysis phase, a fishbone diagram is used to verify all possible potential causes for inaccurate measurements from machine vision system. Then, controllable and non-controllable factors are derived from the diagram.

Fig. 5 shows the fishbone diagram drawn from the observed process conditions. The Taguchi design of experiment was used to validate the effect of the root causes of the output. From the given figure, four controllable factors with three levels and two non-controllable factors with two levels are identified from the fishbone diagram.

The four controllable factors include camera heights, background color, environment light, and gage block. In the controllable factors, the study used three different camera heights to measure parts. Camera height is defined as the distance from the surface of the background to the bottom of the camera. Three distances are shown in Fig. 6, which are 200 mm, 240 mm, and 325 mm. In order to determine the optimum camera height, the three distances include two maximum heights that this system can get in the setup experiments. Additionally, the camera was leveled in every experiment.

Another important controllable factor is environment light. This study used a closed box to isolate the light and a top open box to receive a beam of light. It is illustrated in Fig. 7.

The third controllable factor is gage block. The results from machine vision system can only read in pixels so that calibration setup would make a big difference to the output readings. The team decided to use gage blocks in the calibration setup procedure. In order to get an inch or millimeter reading, more common units of measurement, an image must be registered with a certain part to tell the system how many pixels are equal to the unit of measurement desired. To set up the calibration in this project, the team used gage block to minimize measurement error, which is universally accepted as a precise metrology. Furthermore, black, blue, and red background colors were used in the experiment. For non-controllable factors, different operators, and vibration versus non-vibration were tested in the study. All the factors' hypotheses of the experiment are the following:

- Camera height: H_0:u_{200}= u_{240}= u_{325}, H_1: $u_{200} \neq u_{240} \neq u_{325}$
- Environment (Light): H_0:u_{open}= $u_{closed\ box}$= $u_{top\ open}$, H_1: $u_{open} \neq u_{closed\ box} \neq u_{top\ open}$
- Background color: u_{black}= u_{red}= u_{blue}, H_1: $u_{black} \neq u_{red} \neq u_{blue}$
- Gage block: $u_{0.2"}$= $u_{0.3"}$= $u_{0.35"}$, H_1: $u_{0.2"} \neq u_{0.3"} \neq u_{0.35"}$
- Operator: $u_{operator1}$= $u_{operator2}$, H_1: $u_{operator1} \neq u_{operator2}$
- Vibration: $u_{vibration}$ = $u_{no\ vibration}$, H_1: $u_{vibration} \neq u_{no\ vibration}$

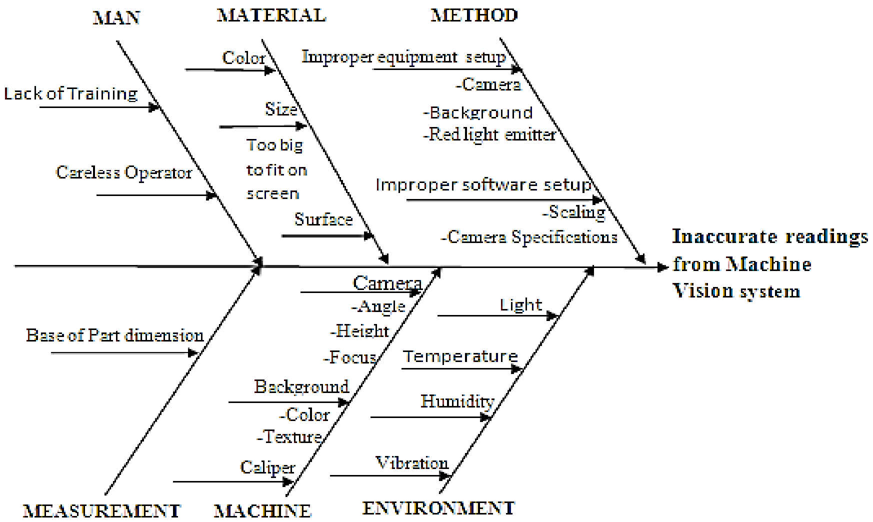


Fig. 5 Fishbone diagram

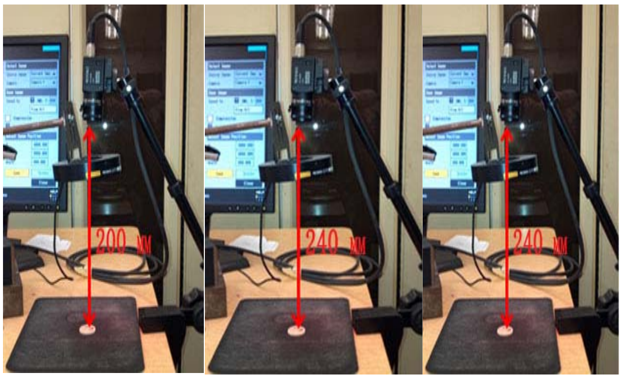


Fig. 6 Camera height controllable factor

Fig. 7 Environment Light Controllable Factor Setup

D.DMAIC Phase 4 – Improve the Current Process

The basis of this phase is the creation of process solutions that reduce or eliminate the root causes identified in Analyze Opportunity. Developing solutions requires analysis; the team used a wide spectrum of tools and techniques, including creative thinking, financial analysis, and change management principles. Ideas and options developed during early stages of this phase were scrutinized for their effectiveness. In the improve phase, the team developed criteria to evaluate the extent to which each of the candidate solutions may impact the controllable and non-controllable factors that were defined in the analyze phase.

Traditional factorial design is commonly used in industry and scientific studies, practically, this method could involve in quantitative experiments with even limited variables [20]. However, Taguchi method allows the analysis of many different parameters without a high amount of experimentations. For example, a process with five variables, each with two levels would require 32 experiments. But, only eight experiments would be needed in Taguchi orthogonal arrays. It combines the experiment of design theory and the quality loss function concept. Both Taguchi's OA (which provides a set of well-balanced experiments with less number of experimental runs) and Taguchi's S/N ratio (which provides logarithmic functions of desired output) serve as objective functions in the optimization process [21]. The S/N ratio depends on the quality characteristics of the product/process to be optimized. The optimal settings are the parameters that always have highest S/N ratios. There are three criteria to evaluate the experiment data. They are nominal the better (NB), lower the better (LB), and higher the better (HB). Based on the quality criteria (NB, LB, HB), the S/N ratio should always be maximized in parameters setting.

In order to find the optimal setting parameters of machine vision from among the parameters that were identified in the analyze phase, the Taguchi design of experiment is executed in the improve phase. The setting parameters that have the highest S/N ratio and nominal accuracy are selected as optimum parameters. All the controllable parameters are categorized into three levels, and the non-controllable parameters are categorized into two levels. They are presented in Figs. 6 and 7, respectively. This project used Taguchi L9 OA for conducting the experiment. The experimental sequence was randomized during the experiment. Taguchi L9 design is as follows in Table III, and the relevant results are showed in Table IV.

TABLE III
DESIGN LAYOUT FOR THE EXPERIMENT USING TAGUCHI L_9 ORTHOGONAL ARRAY

					Operator1		Operator2	
Run	A Light	B Height	C Color	D Gage block	Vib 4 samples	No Vib 4 samples	Vib 4 samples	No Vib 4 samples
1	1(Open)	3(325)	3(Blue)	3(0.35")	y_{111}-y_{114}	y_{115}-y_{118}	y_{121}-y_{124}	y_{125}-y_{128}
2	2(Box)	3(325)	1(Black)	2(0.3")	y_{211}- y_{214}	y_{215}- y_{218}	y_{221}-y_{224}	y_{225}- y_{228}
3	2(Box)	2(240)	3(Blue)	1(0.2")	y_{311}- y_{314}	y_{315}-y_{318}	y_{321}- y_{324}	y_{325}- y_{228}
4	3(Top Open)	2(240)	2(Red)	3(0.35")	y_{411}- y_{414}	y_{415}- y_{418}	y_{421}- y_{424}	y_{425}- y_{428}
5	2(Box)	1(200)	2(Red)	3(0.35")	y_{511}- y_{514}	y_{515}- y_{518}	y_{521}- y_{524}	y_{525}- y_{528}
6	3(Top Open)	1(200)	3(Blue)	2(0.3")	y_{611}- y_{614}	y_{615}- y_{618}	y_{621}- y_{624}	y_{625}- y_{628}
7	1(Open)	2(240)	2(Red)	2(0.3")	y_{711}- y_{714}	y_{715}- y_{718}	y_{721}- y_{724}	y_{725}- y_{728}
8	1(Open)	1(200)	1(Black)	1(0.2")	y_{811}- y_{814}	y_{815}- y_{818}	y_{821}- y_{824}	y_{825}- y_{828}
9	3(Top Open)	3(325)	1(Black)	1(0.2")	y_{911}- y_{914}	y_{915}- y_{918}	y_{921}- y_{924}	y_{925}- y_{928}

TABLE IV
COMPLETED OA WITH EXPERIMENT DATA

Operator 1								Operator 2							
Vib				No Vib				Vib				No Vib			
1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1.776	1.820	1.803	1.735	1.767	1.824	1.802	1.699	1.712	1.794	1.768	1.727	1.721	1.802	1.774	1.731
0.644	0.590	0.545	0.519	0.654	0.587	0.547	0.517	0.596	0.604	0.629	0.608	0.597	0.608	0.626	0.622
-0.243	-0.201	-0.148	-0.147	-0.238	-0.197	-0.152	-0.141	-0.188	-0.178	-0.182	-0.214	-0.196	-0.184	-0.209	-0.195
-0.204	-0.205	-0.176	-0.197	-0.198	-0.199	-0.202	-0.207	-0.150	-0.190	-0.148	-0.162	-0.136	-0.179	-0.153	-0.172
-0.626	-0.622	-0.634	-0.61	-0.613	-0.618	-0.640	-0.635	-0.685	-0.638	-0.595	-0.580	-0.678	-0.645	-0.600	-0.597
-0.250	0.807	-0.268	-0.036	-0.239	0.808	-0.266	-0.043	-0.245	-0.263	-0.252	-0.211	-0.244	-0.269	-0.248	-0.202
-0.711	-0.754	-0.655	-0.583	-0.731	-0.770	-0.648	-0.577	-0.743	-0.714	-0.718	-0.712	-0.729	-0.734	-0.727	-0.716
-0.226	-0.253	-0.129	-0.272	-0.218	-0.247	-0.126	-0.262	-0.268	-0.254	-0.270	-0.250	-0.271	-0.251	-0.273	-0.248
-0.160	-0.147	-0.141	-0.136	-0.137	0.167	-0.119	-0.130	-0.142	-0.143	-0.131	-0.140	-0.157	-0.114	-0.119	-0.005

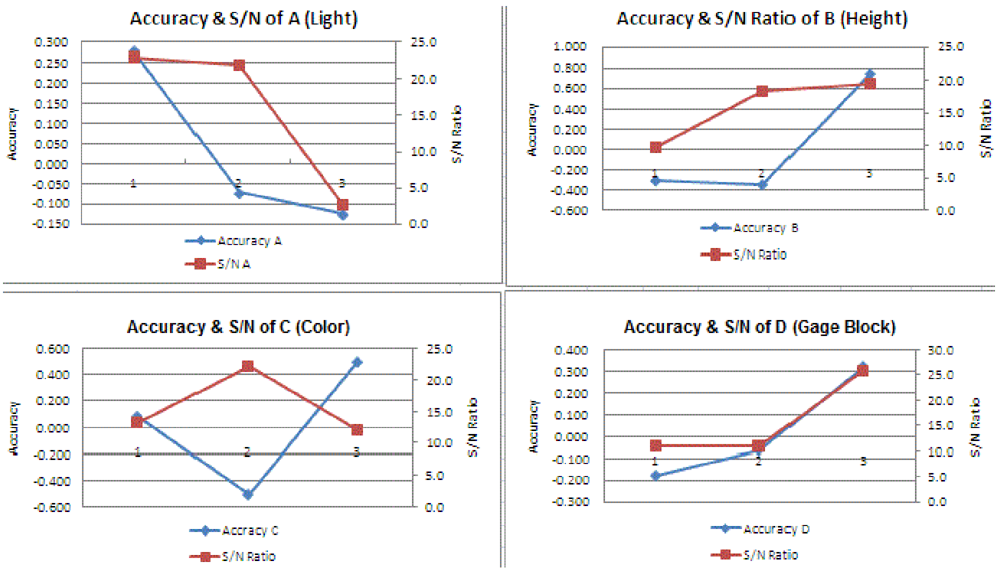


Fig. 8 Accuracy and S/N ratio of environment (light), camera height, background color, and calibration (gage block)

To determine the effect of each variable on the output, the Taguchi S/N ratio method is utilized. In S/N ratio method, since the quality criteria used were nominal the better, the S/N ratio formula used for analysis was (2).

$$\eta = 10\log(\frac{\bar{y}^2}{s^2}) \quad (2)$$

η - S/N ratio; n - Number of measurements (4 here); $\bar{y}$ - Mean of measurements; s - Standard deviation.

TABLE V
TWO-SAMPLE T-TEST FOR VIBRATION AND OPERATOR

T-test for vibration			
Average		Variance	
Vib	No vib	Vib	No vib
0.022	0.029	0.521	0.522
SE	DF	t-value	t α (0.01)
0.120	142	0.055	2.611
T-test for operator			
Average		Variance	
Operator 1	Operator 2	Operator 1	Operator 2
0.046	0.004	0.527	0.516
SE	DF	t-value	t α (0.01)
0.120	142	0.3488	2.611

Table VI shows the accuracy response and S/N ratio response tables. Also, from the data of the Taguchi design of experiment, a two-sample t-test is conducted to conclude the significant impact of operator and vibration. Tests are shown in Table V.

Since the T-values of the T-tests for vibration and operator in Table V are both less than the t-α (0.01) value, the conclusion drawn was that vibration and operator do not have an effect on accuracy.

An interaction plot is a tool to recognize the optimum level setting in each factor after experiments. The interaction plots of four factors, A, B, C, and D, are drawn from the accuracy response and S/N ratio response tables. They are presented in Fig. 8. In this study, since accuracy is nominal the better and S/N Ratio is always the larger the better, the optimum settings are easy to figure out through interaction plots. The accuracies of optimum settings are underlined in Table VI.

TABLE VI
ACCURACY RESPONSE AND S/N RATIO RESPONSE TABLE

Accuracy response				
Level	A	B	C	D
1	0.275	<u>-0.318</u>	<u>0.082</u>	-0.179
2	<u>-0.074</u>	-0.357	-0.502	<u>-0.066</u>
3	-0.126	0.750	0.496	0.320
S/N Ratio				
1	23.0	9.7	13.3	10.9
2	<u>21.9</u>	18.4	<u>22.1</u>	11.0
3	2.7	<u>19.5</u>	12.2	<u>25.8</u>

As presented in Fig. 8, the interaction plots consider nominal the better quality criteria with the S/N ratio always higher the better. Fig. 8 shows the resulting two optimal parameter settings from the accuracy response and S/N Ratio tables. The optima parameter settings are as follows:

Optimal parameter setting 1: closed box, 200 mm camera height, Black background color and 0.3” gage block

Optimal parameter setting 2: closed box, 325 mm camera height, red background color and 0.35” gage block

The prediction accuracy is -0.451 mm in optimal parameter setting 1 and 0.418 mm in optimal parameter setting 2. Since the project has two parameter settings, two confirmation runs were conducted. Two confirmation runs with 10 datasets displayed in Tables VII and VIII respectively.

From Tables VII and VIII, the accuracy from optimal parameter setting 1 has less y_{ijk} average number results (higher accuracy) than optimal parameter setting 2. In this case, optimal parameter setting 1 was utilized to observe the significant factors that influence the accuracy in the following tests. Even though the optimal parameter settings were obtained, it is necessary to analyze which parameter is the most significant one in order to improve the machine vision system’s accuracy during the setup procedure. In statistics, analysis of variance (ANOVA) is a collection of statistical models and their associated procedures in which the observed variance of a particular variable is partitioned into components attributed to different sources of variation. In its simplest form, ANOVA provides a statistical test of whether or not the means of several groups are equal, and therefore, generalizes t-test to more than two groups [22]. So, ANOVA was performed here to analyze the most significant of six existing parameters. ANOVA which was carried out on the S/N ratio values is presented in Table IX.

TABLE VII
FIRST CONFIRMATION RUN WITH OPTIMA PARAMETER SETTING 1 (IN MM)

Accuracy (yijk) from No. 1-10				
1	2	3	4	5
-0.197	-0.228	-0.200	-0.259	-0.186
6	7	8	9	10
-0.225	-0.175	-0.197	-0.161	-0.190

TABLE VIII
SECOND CONFIRMATION RUN WITH OPTIMA PARAMETER SETTING 2 (IN MM)

Accuracy (yijk) from No. 1-10				
1	2	3	4	5
-0.653	-0.701	-0.618	-0.737	-0.613
6	7	8	9	10
-0.626	-0.553	-0.570	-0.672	-0.721

Since the P values of controllable factors are less than 0.01, they are all significant to the output shown in Table IX. Because the P values of the non-controllable factors (Block vibration and Operator) are greater than 0.01, they are not significant to the accuracy. Moreover, since the highest sequential sums of squares appear 9.462 in factor of height, camera height impacts the accuracy of the dimensions from machine vision system and the true dimensions more significantly than other factors.

After observing the accuracy of various heights as in Table X, the accuracy is proportional to the camera height to a certain degree.

After analyzing Table X, camera height was changed to the lowest setting possible in this experiment, which is 150 mm. A new confirmation run was conducted with these parameter settings: Closed box, black background color, 150 mm camera height and 0.3” gage block. The new accuracy is presented in Table XI.

TABLE IX
ANOVA TABLE FOR S/N RATIOS

Source	Degree of freedom	Sequential sums of squares	Adjust square sum	Adjust Mean Square	P value	F value
Light	2	1.143	1.143	0.571	0.000	158.31
Height	2	9.462	2.119	1.059	0.000	293.54
Color	2	4.249	5.727	2.863	0.000	793.36
Gage block	2	3.119	3.120	1.559	0.000	432.13
Vibration	1	0.0004	0.0004	0.016	0.746	4.39
Operator	1	0.016	0.016	0.0004	0.046	0.11
Error	25	0.090	0.090	0.004		

TABLE X
MEASUREMENT ACCURACY IN DIFFERENT HEIGHT

Height	Accuracy
200 mm	-0.318
240 mm	-0.357
325 mm	-0.750

TABLE XI
CONFIRMATION RUN WITH PARAMETER SETTING OF CLOSED BOX, BLACK BACKGROUND COLOR, 150 MM CAMERA HEIGHT AND 0.3" GAGE BLOCK (IN MM)

Accuracy (yijk) from No. 1-10				
1	2	3	4	5
0.010	-0.011	0.004	0.004	0.003
6	7	8	9	10
0.036	0.02	0.045	0.015	0.007

After the confirmation run with the new optimum parameters, the experiment gained a new accuracy confidence interval, which is (-0.00020, 0.0268) mm. The new accuracy confidence interval includes 0, which is the accuracy project sought in the experiment. It means that, after optimizing its parameters, the machine vision system can be accurate enough to measure precise parts. Through improving machine vision system, this study provides systematic procedures to implement Six Sigma effectively.

E. DMAIC Phase 5 – Control Performance

The purpose of the control phase is to maintain the improvements made by the improve phase. Maintaining the results from the above phase is difficult due to many variable factors. It is necessary to set up some standard operating procedures for operators to sustain these improvements. Control charts are a powerful tool to ensure improvements. X-bar and R charts were introduced for monitoring the process along with a control plan to deal with special causes of variation. Training is provided for the operator working with the process so that they can record control charts to check the stability of the new machine vision system. X-bar and R chart templates based on this experiment's setup parameters are shown in Fig. 9.

Instructions for using SPC chart:

Step1. To be consistent with the baseline data, every two hours the operator takes five samples randomly, beginning at 8:00 A.M., and calculates and records the dimension variances between CMM and machine vision system (yijk). There are five subsets because there are five samples. For each subset, there are four data because the operator takes samples four times every day. The difference between CMM and MV reading is accuracy (value of X in the form). The operator notes them in the form in Fig. 9.

Step2. Similarly, note the accuracy measurements daily at 10:00 A.M., 12:00 P.M., and 2:00 P.M.

Step3. Calculate the mean and range of each subset. Once these values are calculated, the average (x-bar) and range (R) are calculated. These values are simply the means of each subset's mean and range. Note down in the form of Fig. 9.

Step4. Plot average numbers in X-bar char, range numbers in R chart. Observe whether these plots run inside the control limits (UCL, LCL). If they run outside the control limits, stop the process and check what is going wrong.

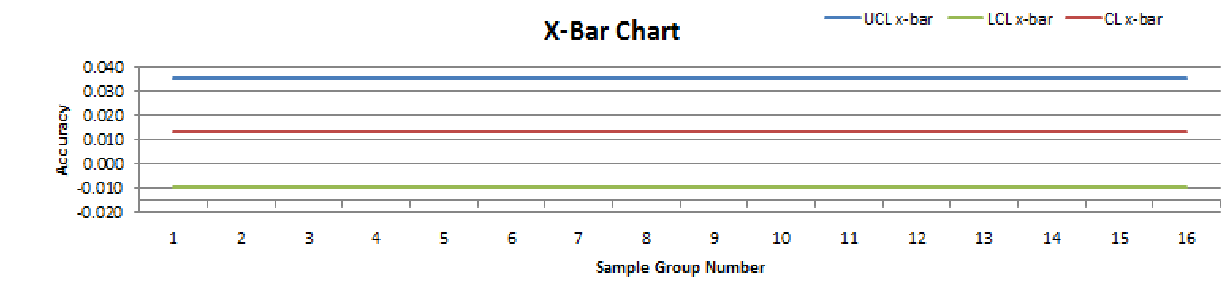
IV. CONCLUSION

This case study demonstrated a systematic methodology of DMAIC and Taguchi design of experiment to optimize the setup parameters of machine vision system. A team was formed to improve the poor current setup condition of machine vision system. It analyzed the impact of four different controllable factors and two non-controllable factors. As a result, the confidence interval improved from (-0.1786, -0.2250) mm to (-0.0002, 0.0268) mm. The conclusions of the case study can be stated as follows:

1. The case study used DMAIC and Taguchi design of experiment results in the accuracy of the measurements from machine vision system improved to be within (-0.0002, 0.0268) mm. It shows that the machine vision system is as accurate as possible after six sigma DMAIC optimization process.
2. The GRR study revealed important results while collecting a certain amount of data. It indicates that the main reason causing an inaccurate machine vision system is equipment accuracy, which is related to machine parameter setup procedures.
3. The use of DMAIC methodology showed the power of a systematic methodology for finding out the root causes and addressing a challenging problem. It effectively improved the current system. In addition, the Taguchi method is a useful strategy to optimize systems through reducing variables.

The results of this project suggest that implementing the DMAIC approach and the Taguchi method can provide an optimal option to enable managers to reorient parameter settings of production processes.

Operator			Part #													
Date																
Time of Day	8	10	12	2	8	10	12	2	8	10	12	2	8	10	12	2
Sample Group #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Sample Measurements Value of X 1																
2																
3																
4																
5																
Sum																
Average (X-bar)																
Range (R)																



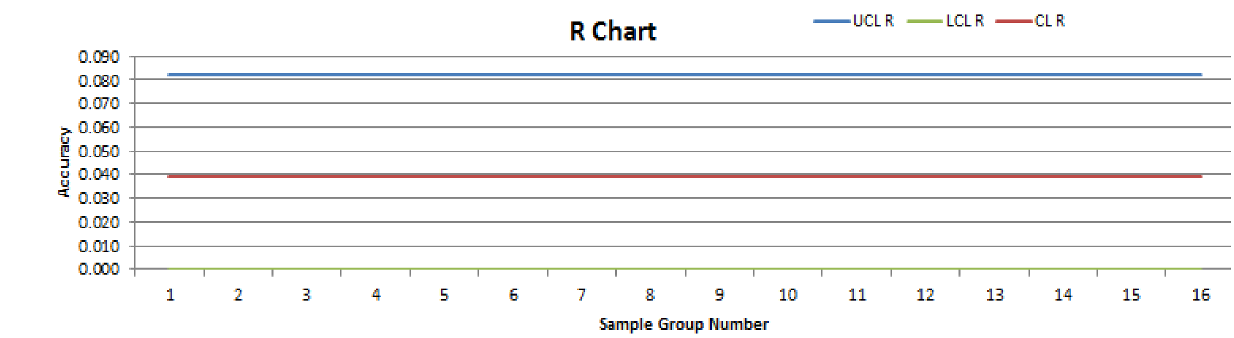


Fig. 9 Process Control Chart

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