Model-Based Optoelectronic Packaging Automation

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***Abstract*—In this paper, we present an automation technique that yields high-performance, low-cost optoelectronic alignment and packaging through the use of intelligent control theory and system-level modeling. The control loop design is based on model-based control, previously popularized in process and other control industries. The approach is to build an *a priori* knowledge model, specific to the assembled package's optical power propagation characteristics, and use this to set the initial "feed-forward" conditions of the automation system. In addition to this feed-forward model, the controller is designed with feedback components, along with the inclusion of a built in optical power sensor. The optical modeling is performed with the rigorous scalar Rayleigh–Sommerfeld formulation, efficiently solved online using an angular spectrum technique. One of the benefits of using a knowledge-based control technique is that the efficiency of the automation process can be increased, as the number of alignment steps can be greatly reduced. An additional benefit of this technique is that it can reduce the possibility that attachment between optical components will occur at local power maximums, instead of the global maximum of the power distribution. Therefore, the technique improves system performance, while reducing the overall cost of the automation process.**

***Index Terms*—Alignment, optical microsystems, optical modeling and simulation, packaging, photonic automation.**

I. Introduction

THE current trend in optical microsystem design is to exploit advanced devices and new system architectures to achieve greater system performance, such as higher data rates or brighter displays. However, to push toward the theoretical limits of optical microsystems, accurate alignment and packaging of the multidomain system is required. Packaging is a challenging problem, as systems are typically manually aligned. This technique is labor intensive, slow, and can lead to poor performance of the system. Even with the recent progress in the development of devices and microsystems, the packaging and assembly of these systems remains as the possible critical limiting factor to commercial success. These problems, compounded with the current economic struggles of the telecommunication community, result in a high cost to develop, prototype, and commercialize the next generation of optical microsystems.

Automation is the key to high-volume, low-cost, and high-consistency manufacturing, while ensuring performance, reliability, and quality. There is a growing interest in the development of automation techniques for photonic alignment and packaging, as the optical microsystem industry desires the benefits of automation experienced by the semiconductor industry. However, the photonic community cannot simply use the same automation processes as the mature semiconductor industry. The equipment is not optimized for optoelectronic packaging automation, since the optical and geometric axes of these optical microsystems are often not aligned. There is a fundamental difference between electrical or semiconductor automation and optical automation. In the electrical domain, a good attachment occurs between two components when they physically touch and solder flows between them. However, in the optical domain, not only is a good connection needed, an exact orientation alignment is required. As a result, packaging costs currently accounts for 60%–80% of the entire photonic component cost [1].

We are developing an automation process for the assembly, manufacturing, and packaging of optical microsystems using advanced device specific optical power models as well as intelligent control theory to yield high-performance, low-cost packaging. *A priori* device and process knowledge will be exploited in online control loops to align fibers and components in a near-optimal configuration to maximize power transmission. Our technique incorporates the materials and mechanics in order to position the components and devices, exerting forces on the various degrees of freedom before, during, and after alignment so that the optical signal is positioned for maximum transmission in a robust manner.

Using the model-based control process, we are presenting a new paradigm for photonic automation. Our technique will increase the system performance and efficiency of the automation process, while decreasing the cost of optical microsystems. This technique will employ existing capital equipment infrastructure (from semiconductor and industrial automation) and increase the system performance in terms of bit-error rate (BER), signal-to-noise ratio (SNR), insertion loss, crosstalk, and coupling. As device and system designs become more complex, the advantages of our technique will be magnified.

In this paper, we first present the current industry state-of-the-art photonic automation systems. We use this section to define common terms and techniques before introducing our optical automation research and presenting its potential economic and performance advantages. We next discuss our system-level optical modeling technique and present two examples of knowledge-based control technique for the automation of photonic systems. We close with brief conclusions and a discussion of future work.

II. Photonic Automation Manufacturing Process

Before introducing our automation process in detail, we first present the current industry state-of-the-art photonic automation process and show the limitations of technique. From this discussion, the performance and potential economic advantages of our technique will be clear.

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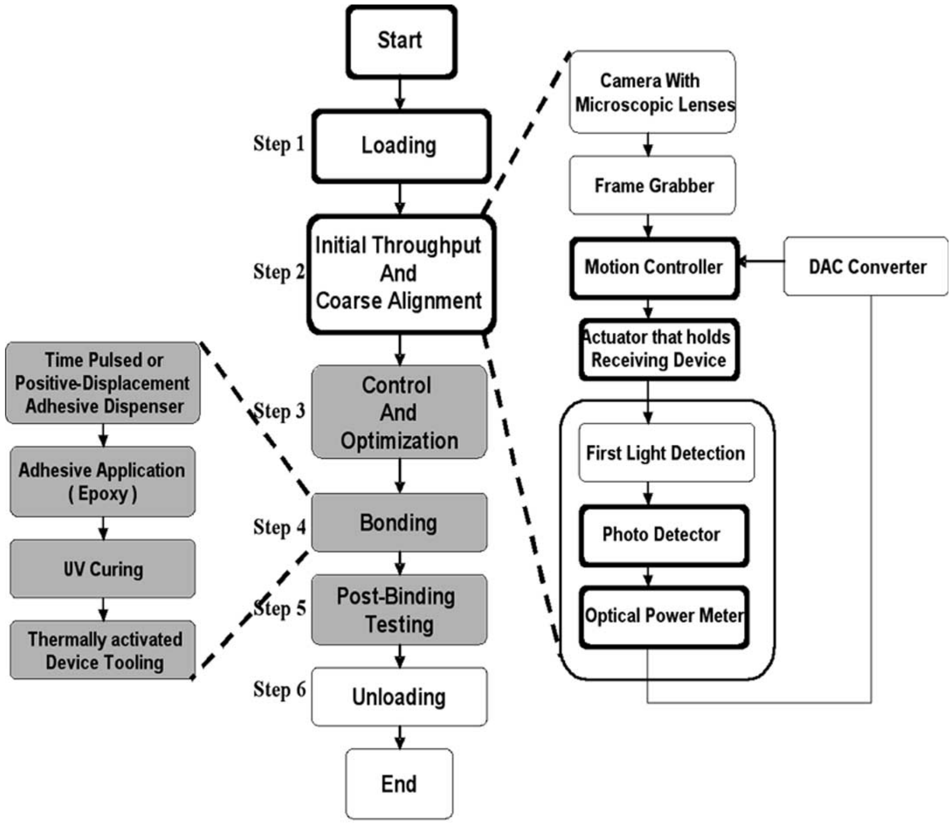

Fig. 1. Current state-of-the-art photonic automation.

A. *Current State-of-the-Art Photonic Automation Process*

Current photonic automation is used to couple laser diodes to fiber, fiber to fiber, or waveguide (on an IC) to a fiber [2]. The techniques are typically based on the mature industrial and semiconductor automation, robotics, motion control, sensors, and capital equipment. To date, no significant defined process has been developed to implement automation for general optical systems; therefore, the majority of these production lines are poorly automated. However, photonic automation research has been performed in academic institutions, for example, examining how packaging and alignment can be designed in the system substrate through micromaching [3]. In addition, some leading automation and optical component companies have realized the importance of automation for photonic systems, as product development has begun at Newport, Irvine, CA [4], Kyocera, San Diego, CA [5], Polytech PI, Karlsruhe, Germany [6], and Palomar, San Diego, CA [7]. This work is promising for the support of optical automation for simple unimodal power distributions, such as Gaussian shaped beams emitted from laser sources, waveguides, and fibers.

In Fig. 1, we present a flow diagram of the current manufacturing automation process for photonic devices. We provide brief details of each step. In step 1, the device is *loaded* into the machinery using standard automation pick and place [1]. Reproducible, damage-free insertion of the fibers and fiber arrays and waveguide chips can be obtained through the use of precision device tooling and high-magnification video feedback. Step 2, *first light detection and coarse alignment*, is achieved using a camera vision system and signal processing to locate the positions of the fiber and the device. Step 3, *control and optimization*, fine-tunes the position of the alignment. This step is discussed in detail in the next section, as it is the crux of our automation process. Step 4, *bonding*, is the application of commercial-grade and user-proprietary optical adhesives. It is injected via a time-pulsed or positive-displacement adhesive dispenser. Calibrated UV radiation is delivered via dual fiber-optic illuminators for curing. In step 5, *postbonding testing*, final throughput measurements are made to quantify bond shift and validate device quality. Finally, in step 6, the device is *unloaded*. In Fig. 1, the shaded boxes are the specific parts of the process in which we have implemented our knowledge-based technique.

B. *Current State-of-the-Art Photonic Automation Control*

As introduced in Fig. 1, step 3 of the manufacturing process is the key to the performance of the packaged device. In this step, the alignment of the critical optical components is controlled to achieve maximum performance. The currently implemented control loop is described in [8] and presented in Fig. 2. The technique is based on a combination of visual inspection and power alignments [9], since proportional integral derivative (PID) loops [10] converge in a single mode: simple unimode power distributions. Fig. 2 includes an off-the-shelf motion controller often referred to as the servo-feedback control loop. This controller executes a proportional (P) or proportional, derivative integral (PID) control algorithm [8].

The control loop is initiated by a vision system, as seen in step 2 of the flow diagram shown in Fig. 1. After determining

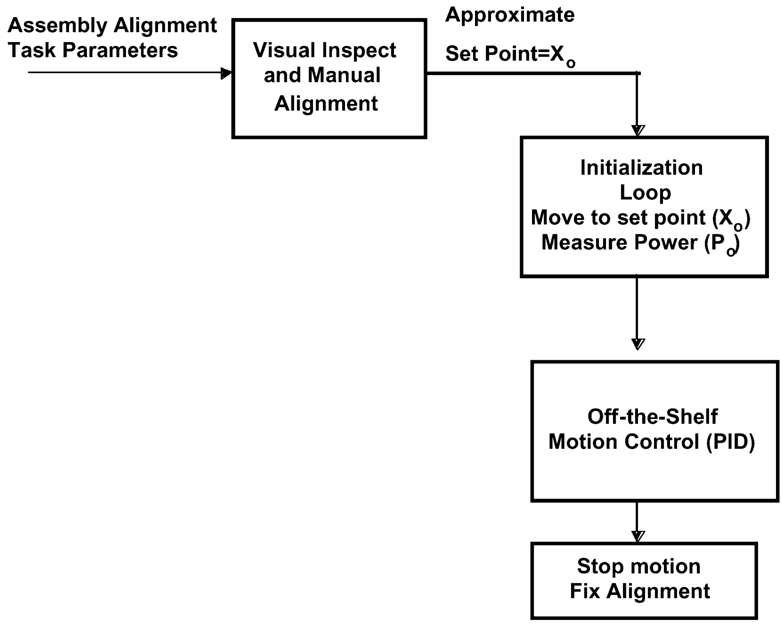

Fig. 2. State-of-the-art photonic automation control.

the vision set point, x_0 in Fig. 2, the alignment is fine-tuned with the motion controller. Each axis of motion is independently controlled, and typically, the number of controlled axes is quite small. To obtain the required power measurement, a laser excites the system and a power meter is attached to the output fiber. In efforts to decrease the amount of time to determine the peak power mode, more efficient positioning algorithms have been implemented, based on the assumption that the power distribution will always be a unimode or Gaussian shape [11]. However, even these recent "smarter" techniques [6], [9] are not model based and, therefore, cannot exploit device model knowledge to enhance performance.

This state-of-the-art automation control process has many limitations. First, if the optical wavefront is not a symmetric unimode function, the control algorithm can get "caught" at local power maximums instead of the global maximum of the entire wavefront. This error can yield a dramatic loss in power efficiency, SNR, and BER for the assembled product. Therefore, as the complexity of the optical wavefront increases (i.e., non-Gaussian) with the addition of complex devices, such as microelectromechanical systems (MEMS) and diffractive optical elements (DOE), this current technique of alignment will not provide accurate and efficient results. Second, since multispace searches are employed with a gradient ascent algorithm, the convergence time of the alignment equipment will depend on factors such as the control resolution and processing power. Packages with multiple degrees of freedom may result in a delayed assembly line, since the gradient ascent algorithm for multiple axes is very slow and sometimes nonconverging, which increases the cost of the automation process. Finally, current servos and control (PID) deployed in the semiconductor equipment do not employ process knowledge base data in the loop. Due to the limitations of the current automation techniques, the need for a knowledge-based modeling process for the automation of photonic systems is required to reach the potential of the high-capacity optical systems in which packaging and automation is a key to performance and cost.

III. Background and Motivation: Model-Based Automation for Optical Microsystems

In contrast to the current automation techniques, we are developing a new automation process for the packaging, aligning, and attachment of optical fibers and waveguides to devices by employing a model-based control algorithm based on the optical power distribution of the specific devices and optical propagation paths. This power distribution model predicts the optimal alignment and attachment for a given application, while, in conjunction, a completely automated active optical feedback loop ensures an accurate, efficient, and robust connection without the need of human inspection and testing. Not only will this decrease the cost of system alignment and packaging, our technique will employ existing capital equipment infrastructure (from semiconductor and industrial automation) and increase the system performance in terms of BER, SNR, insertion loss, crosstalk, and coupling. To the best of our knowledge, no model-based controller design has been employed in optoelectronic assembly to date. In this section, we introduce our method and compare it with today's standard, highlighting the advantages of our technique.

A. Approach and Strategy

The key to our approach is in the design of a model-based control loop for photonic automation, replacing step 3 in the manufacturing process shown in Fig. 1. Therefore, we find it appropriate to define the idea of model-based control. The overwhelming majority of currently deployed control loops are of the simple feedback type, including P, proportional and integral (PI), or PID. However, in addition to the feedback module, the model-based controller also includes a "feed-forward" element,

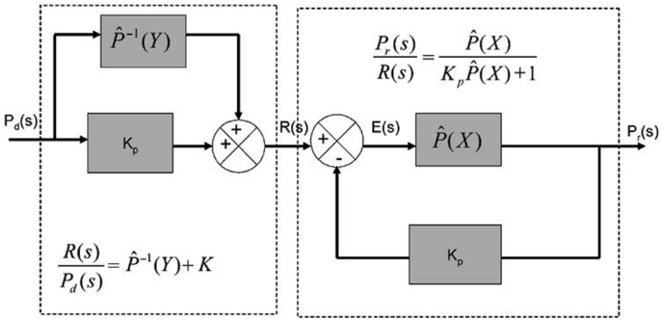

Fig. 3. Simple model-based control.

which acts as a set point modification procedure. The feed-forward element is typically based upon *a priori* knowledge regarding the process to be controlled. Such a controller is denoted as a model-based controller. This family of controllers include model reference adaptive control (MRAC) [12], [13], internal model control (IMC) [14], model predictive control (MPC) [15], and intelligent control such as expert control, neurocontrol [16], and fuzzy logic control [17].

In our automation process, we increase the accuracy, performance, and efficiency of packaging complex optical systems through the use of *a priori* knowledge gained by optical system simulation. The simulation will predict the complex optical wavefront at the coupling points, leading to the ideal positioning of the devices for optimal alignment. With this advanced knowledge, the "feed-forward" stage of our control loop sets the alignment position of the system. From this position, fine-tuning of the alignment and attachment can be achieved with similar techniques, such as a PID feedback loop.

The advantage of model-based control and the use of a feed-forward loop is seen in Fig. 3. If an accurate model of the control plant $\hat{P}$ and its inverse $\hat{P}^{-1}$ can be determined, the control loop can position the mechanics to at the vicinity of the globally optimal configuration. In Fig. 3, the transfer functions of each of the subloops are given. If $\hat{P} = P$, where P is the behavior of the plant, perfect tracking can be achieved by

$$\begin{aligned}\frac{P_r(s)}{P_d(s)} &= \frac{R(s)}{P_d(s)} \cdot \frac{P_r(s)}{R(s)} = \hat{P}^{-1}(Y) + K_p \frac{\hat{P}(X)}{K_p\hat{P}(X)+1} \\ &= \hat{P}^{-1}(\hat{P}(X)) + K_p \frac{\hat{P}(X)}{K_p\hat{P}(X)+1} \\ &= \frac{1+K_p\hat{P}(X)}{K_p\hat{P}(X)+1} = 1\end{aligned} \tag{1}$$

where, $P_r(s)$ is the output power received on the power meter, $P_d(s)$ is the input desired power to be tracked, and $R(s)$ is the intermediate signal between the feed-forward loop and the feedback loop. Each of the signals is in the frequency domain.

The issue of developing an inverse model for a given dynamic system or transfer function has several practical challenges [14]. Most transfer functions are not invertible, either due to their nonminimum phase (having zeros at the right half plane) nature or due to the excess of poles over zeros of P, which results in demanding online differentiation (noisy) process. Nevertheless, in many situations it is practical to obtain a realizable and local inverse. We discuss the finding of a practical approximation to the inverse model in the next section.

Using a knowledge-based control technique provides many advantages over the current photonic automation techniques. We can support the packaging of systems not emitting optical power in an ideal unimode power distribution. Therefore, if the optical power distribution has many peaks and valleys, we know *a priori* which peak will nominally contain the most optical power. From the position of the peak, optimal alignment can be obtained, as our control loop avoids finding and being positioned in local power maximums. Unavoidable errors, such as manufacturing errors and misalignments, will be partially corrected with a PID feedback loop, found in addition to the feed-forward loop. An additional advantage of our technique is the time that the automation control loop takes to track the peak power position. We can greatly decrease this time with the feed-forward block of our algorithm. Using results from advanced simulation, we can get close to the optimal position without having to search a complete optical field space. This reduces the required field of view and required resolution, which can lower the cost of the automation sensors, software, and hardware. As the number of packages to be assembled increases, the packaging time of an individual device is critical. This time directly affects the packing time of the entire lot of devices, which is critical for large manufacturing runs.

For example, having *a priori* knowledge of how tilts of the fiber or waveguide affect the performance of the system is critical. Tilts are the most challenging aspect of alignment using the current methods, as the control loop dramatically slows down as the number of parameters to optimize the alignment position increases [7]. With our model-based control, we can reduce the costly time of optimizing tilted, and more generally, multiaxis systems.

Our control strategy is shown in Fig. 4. There are three main "loops" or phases shown in the figure. The inner most loop, denoted (A) in the figure, is the same off-the-shelf servo feedback loop described in Fig. 2. However, in this case, the servo loop is initialized with a different, more advanced set point, described below.

The two other loops are the essence of our method. The "feed-forward loop," denoted (B) in Fig. 4, provides the inner servo loop with a "smart" set point to track. This set point is determined by a properly derived, optical power propagation model computed online or, if required, can be stored in a database. The optical power propagation model is device and assembly task specific; that is, different devices with different alignment and assembly tasks will possess unique power distribution functions. As new assembly tasks are submitted to the control machinery, that is, inputs to the feed-forward block, the model is activated and generates a new set point for the inner feedback servo loop to track and lock on. We emphasize that x_0 generated by our method (see Fig. 4) will, in general, be different from the value of x_0 currently produced by the state-of-the-art controller seen in Fig. 2. This new x_0 position forecasts the model-based nominal configuration for maximum power transfer.

The third and final loop is called the learning loop, denoted (C) in Fig. 4. This loop is the outermost loop, which provides opportunities for the system to improve upon its power model

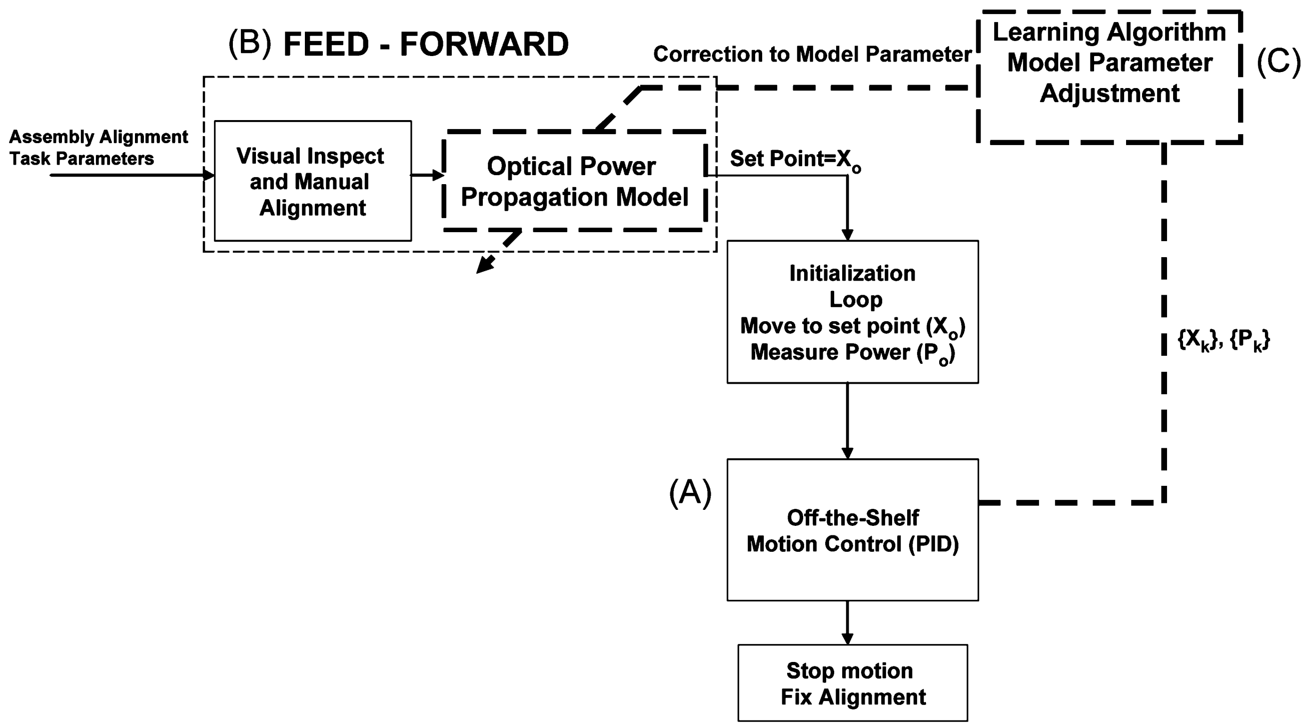

Fig. 4. Knowledge-based control algorithm for automation of photonic systems.

and adjust its accuracy on the basis of "experienced evidence" or a mismatch between expected power and measured power at a specific axes configuration. The learning loop only gets activated at a lower sampling frequency for specific and appropriate tasks.

IV. Optical Modeling Technique

As part of the automation process, appropriate online optical modeling techniques must be incorporated into our knowledge-based controller. It is critical to acknowledge that the appropriate optical modeling process varies for different devices and systems. The model is to be "online," that is, computationally efficient, such that many different system configurations can be simulated to find the position and alignment that creates the best system performance. However, the more accurate the optical model, the more effective our model-based automation process is in increasing performance and productivity, while reducing the high packaging costs. Therefore, the optical model used in our automation process needs to be both accurate and computationally efficient.

When optical wavefronts interact with the small feature sizes of optical microsystems, many of the common optical propagation modeling techniques become invalid, and full vector solutions to Maxwell's equations are required for accurate simulation [18]. However, these accurate solutions are computationally intensive, disabling the use of online models. To reduce the computational resources of modeling the optical wavefront in free space by the vector solutions, a scalar representation is commonly used. We have been using the Rayleigh–Sommerfeld scalar formulation, efficiently solved by the angular spectrum method [19], [20] for our online models. We have previously shown that far (Fraunhofer) and near (Fresnel) field approximations, which can further reduce the computational demand of scalar solutions, are not valid for typical microsystem dimensions [21].

It is to be acknowledged that there are good models and simulation tools from third-party vendors such as ZEMAX, OSLO, and BeamProp. However, these models would have to be customized for our online control process. Using some of these tools, could be helpful in the optical modeling process; however, the creation of tools for our specific use is proving more beneficial.

A. Determination of the Inverse Model

As shown in the previous section, determining the inverse model is crucial to the success of the feed-forward method. Procedures for finding the inverse solutions of problems involving such nonlinear systems as our complex power distributions are, in general, extremely complicated. The challenge in determining the inverse model for nonlinear functions is that there is not a one-to-one mapping of the variables. This can be seen in the power distribution in Fig. 5, as for any given value of y, there could be more than one x value.

Because of the complexity of inverting nonlinear systems, it is often necessary to introduce an "equivalent" set of monotonic functions in place of a multimodal function. Each monotonic function in the set is only valid in a defined range. We currently find the inverse model for our control algorithm by decomposing the power distribution waveform into piecewise linear (PWL) segments. In the control loop, a feedback signal to the inverse model block determines which range, or PWL segment, should be used for the calculation of the inverse model. The PWL representation for a complex power distribution is

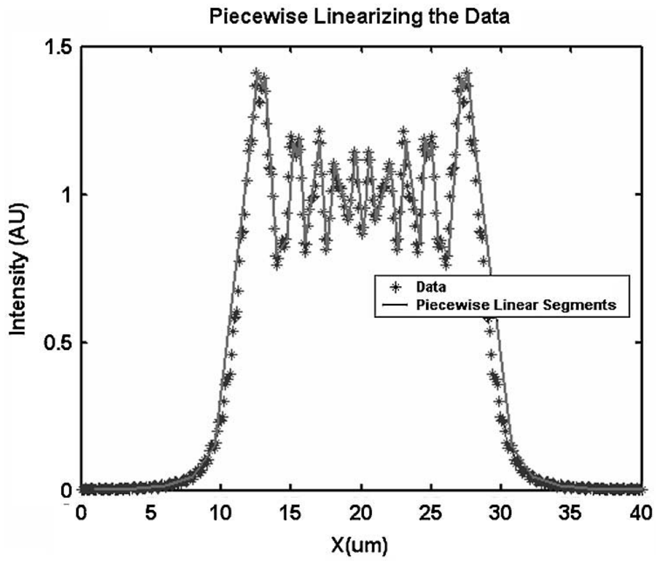

Fig. 5. PWL segments of the optical power distribution.

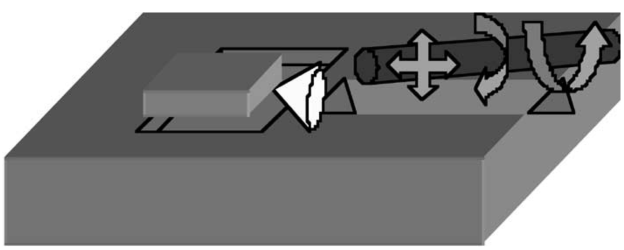

Fig. 6. Edge-emitting laser coupled to a fiber.

shown in Fig. 5 (denoted by the * symbol). This power distribution and its inverse are used in the examples presented next.

V. Preliminary Examples and Analysis

A. Coupling an Edge-Emitting Diode to a Fiber

To highlight some of the advantages of our knowledge-based automation process, we present preliminary examples comparing our technique and the currently used state-of-the-art control algorithms presented in the previous section. In this example, we present the coupling of an edge-emitting laser diode to an optical fiber. We choose this example, since this is one of the most commonly packaged devices using the current optical automation process [1]. In this example, the GaAs laser diode is flip-chip bonded onto an Si bench, containing the electrical drivers for the laser, along with a fabricated V-grove for placement of the fiber. The V-grove provides "self-alignment" for the fiber; however, within the V-grove, the positioning of the fiber is critical to the final performance of the device. The device is seen in Fig. 6. The arrows represent the six degrees of freedom [both two-dimensional (2-D) and three-dimensional (3-D)] in which the fiber needs to be aligned.

In this example, we assume that the laser diode emits a broad Gaussian beam, which propagates through a 20×20 μm square aperture to a fiber with a 4-μm core. We use the aperture in this example to ensure the power distribution is not a simple

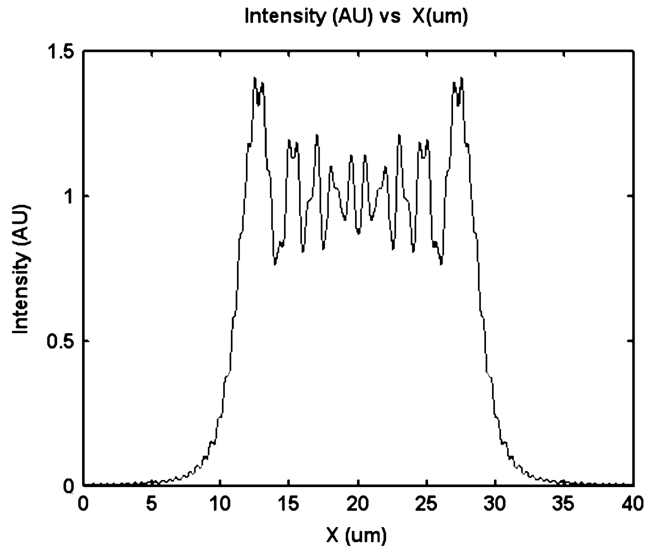

Fig. 7. Power distribution simulation at the fiber interface.

unimode. The distance of propagation between laser diode and fiber is only 10 μm; therefore, the light has propagated only into the near field, and its 2-D intensity pattern in an observation plane at the fiber shows diffractive effects, as seen in Fig. 7. This result is determined from our angular spectrum simulation and verified in [18].

We first analyze the control loop with the current state-of-the-art method. As discussed in Section II and Fig. 2, the current state-of-the-art automation process determines an initial set point in the V-grove through the visualization of the fiber to the aperture, aligning the geometrical optical axis with the center of the fiber core (at a location of 20 μm in Fig. 7). From this set point, in step 3, the gradient ascent algorithm is performed to find the position alignment for maximum power coupled into the fiber.

In contrast, we use a knowledge-based control technique in step 3 to determine the positional alignment for the maximum power coupled into the fiber. Therefore, we start by simulating the entire system to predict the best feed-forward set point for our control algorithm. The simulation is performed using our angular spectrum technique [19], [20], as the output intensity distribution and a distribution of the power coupled into the fiber are determined. In this example, we define the feed-forward set point with the simulated position of the maximum power (area underneath the intensity curve) captured in the 4-μm fiber, seen in Fig. 8(a). The position is found at (13.8, 13.8 μm).

In Fig. 8(b), we compare the coupling of the fiber using the current state-of-the-art technique and our knowledge-based control algorithm. The current technique starts at a position close to the center of the geometrical optical axis (20, 20 μm) and uses the gradient ascent algorithm (Fig. 2), which stops the alignment loop at a local maximum power, denoted by the "X" in the figure. In contrast, our knowledge-based control technique starts at the feed-forward position (13.8, 13.8 μm) and uses a gradient ascent algorithm to find the global maximum power coupled into the fiber, denoted by the "O" in the figure (actually, in this example, the algorithm starts off from the set point by a couple of micrometers to simulate possible mechanical and

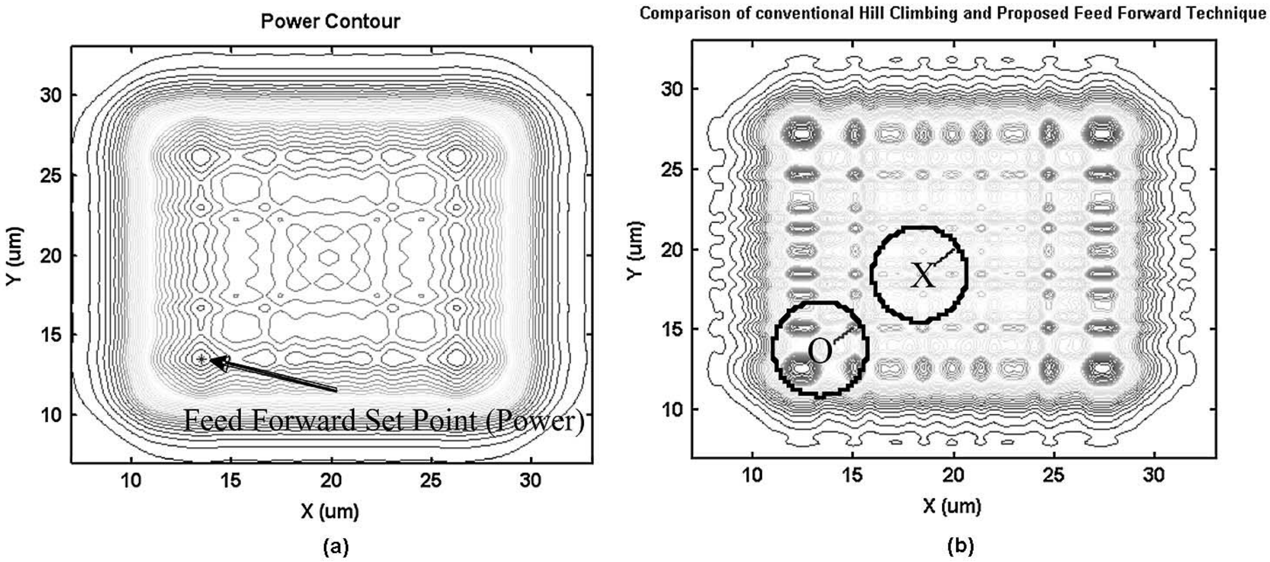

Fig. 8. (a) Contour diagram of the power coupled into an 4-μm fiber determines the feed-forward set point. (b) Intensity contour of wavefront with superimposed final fiber positions using the current state-of-the-art technique ("X") and our knowledge-based control algorithm ("O"). Using our proposed technique, we show an improved system performance of approximately 18%.

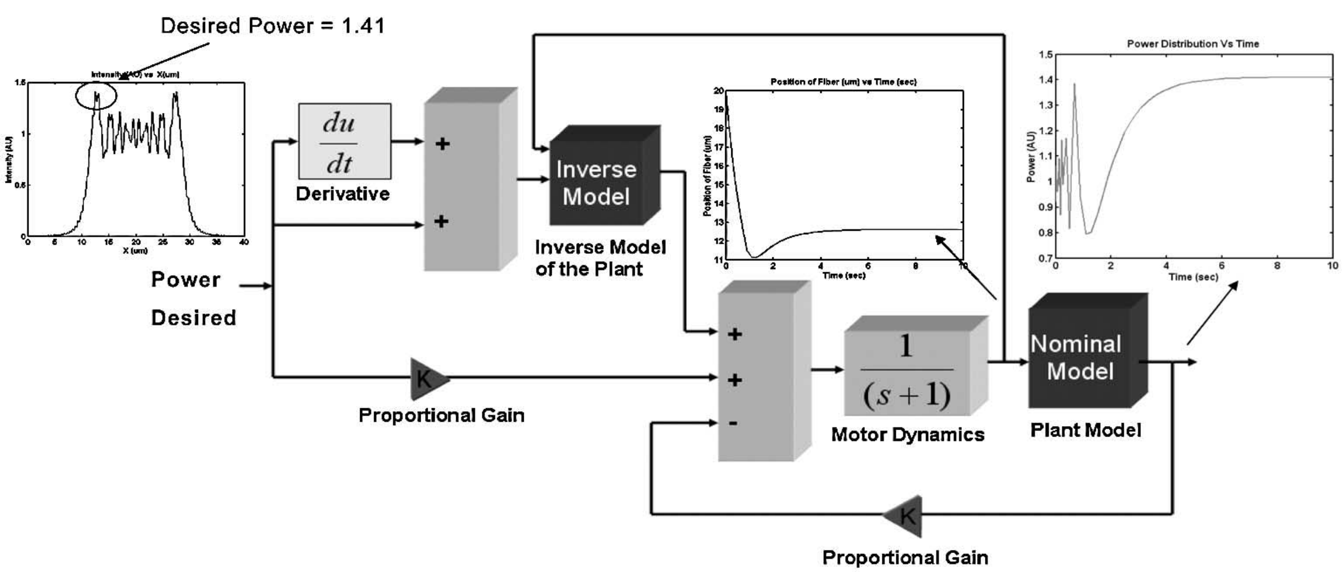

Fig. 9. Control process including the feed-forward loop and simulation results for the specific laser-to-fiber example.

system misalignments). The paths of the gradient ascent algorithms for both our method and the classical method are included on the intensity diagram in Fig. 8(b). In this example, we show an increase in system performance of approximately 18% when using our knowledge-based technique over the current automation techniques.

Using the same laser diode-to-fiber coupling example, we present a complete simulation of our proposed automation control process, seen in Fig. 9. Again, an online simulation is performed at the point of attachment. For these online simulations, the maximum throughput power for the ideal positional alignment of the fiber is determined. This is used as a target or tracking parameter. In this simulation, we use our angular spectrum optical modeling technique [19], [20] and determine a peak intensity value of 1.41 (AU). The inverse model is calculated with the PWL deconstruction as presented in the previous section. Using a simple $1/(s+1)$ motor dynamic, we simulate the entire control loop in MATLAB's Simulink. Also included in Fig. 9 are simulation results, in terms of optical power received versus time and motor position versus time. Note that for these control parameters, the position of the motor settles at a distance of 12.6 μm, which tracks our goal intensity value of 1.41, in approximately 7 s.

B. Fiber Array Automation

In this example, we analyze the automation process of aligning and attaching an eight-element fiber array to a star coupler, shown in Fig. 10. The spacing between the waveguides and the fibers in the fiber array are matched to increase system performance. To make the system more realistic, we excite the star coupler input with an optical pulse, having a tilt of 2°. This is a reasonably expected tilt misalignment during a current

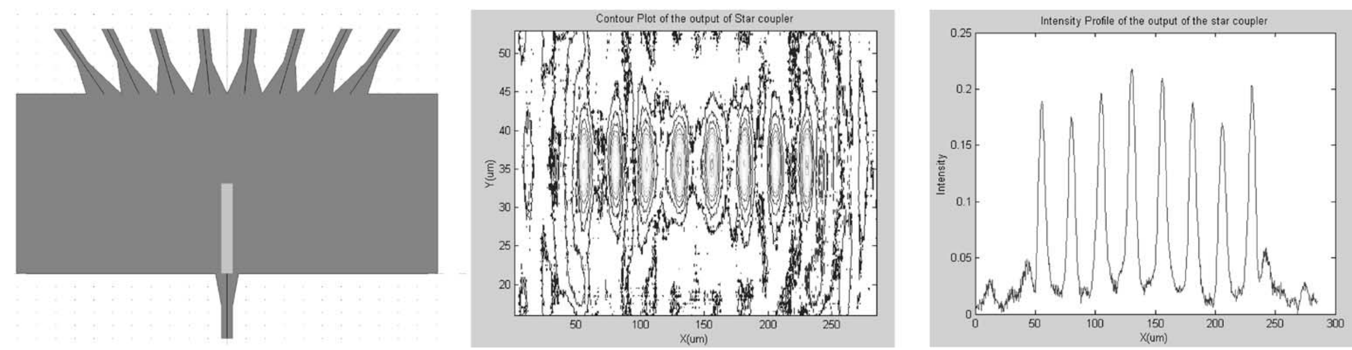

Fig. 10. Star coupler and optical intensity contours shown in 3-D and 2-D.

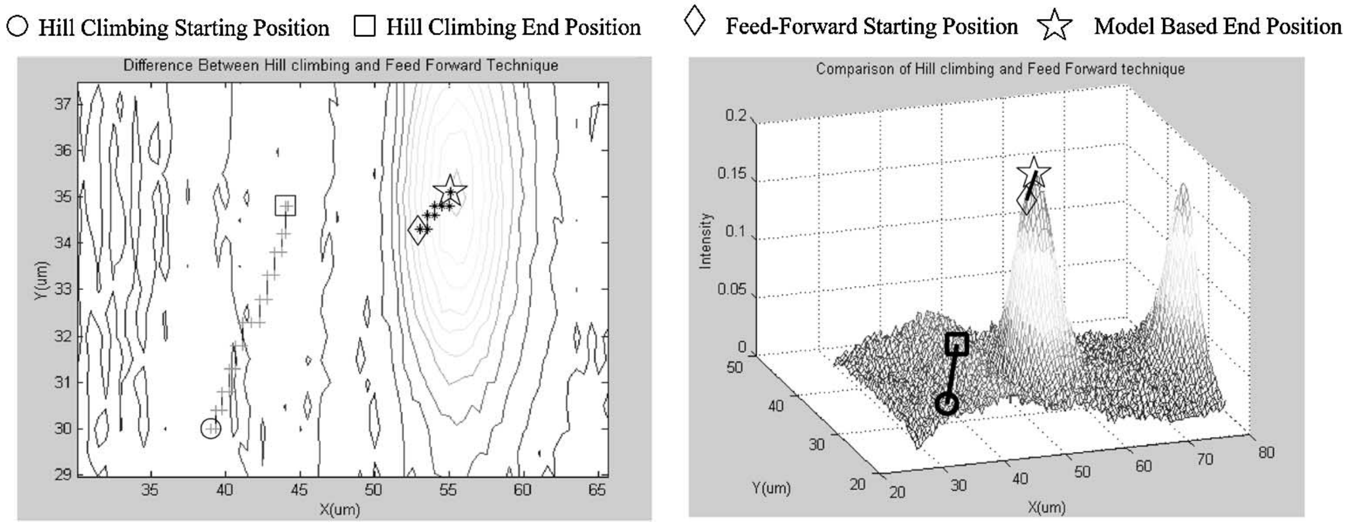

Fig. 11. Comparison of our knowledge-based control method versus existing alignment control.

semiautomatic assembly process [9], [6]. With the use of simulation we can determine *a priori* the output wavefront that is expected from the star coupler. The 3-D and 2-D cross-section intensity contours, simulated in RSoft's BeamProp [22], are shown at the edge of the output of the star coupler and seen in Fig. 10.

As we did in the first example, we first perform the current industry standard for alignment and packaging automation (visualization setpoint and gradient ascent, described in Section II and Fig. 2) for comparison with our model-based control technique. As we saw in the previous example, a possible error can occur by positioning the first fiber at a local maximum. This is shown in Fig. 11, as both a 2-D intensity contour and a 3-D figure. The hill-climbing algorithm is started at a position, denoted by the circle in Fig. 11, which is roughly half the fiber array pitch spacing, in both the x and y direction, and runs until a maximum is determined. In this example, this technique, "zigzags" and stops at a local maxima (denoted by the square) before the global peak power for the first fiber. The peak intensity at this local position is 0.0502 (AU).

In contrast, the results from the knowledge-based control approach is also shown in Fig. 11, denoted by the path marked with the * symbol. From the device model simulation, the feed-forward control block determines where the maximum power peak will occur and sets this initial position in the control loop. In this example, we position the initial point roughly 5% away from the maximum value to simulate the possibility of optical modeling errors, equipment misalignments, and/or manufacturing tolerances. This technique quickly finds the maximum power for coupling to the first fiber in the array, which is denoted by a star in Fig. 11. The peak optical intensity found at this peak is 0.2376 (AU), which is an increase of over 370% over today's current method.

Besides finding the global maximum power peak, our technique is more efficient when compared to the current state-of-the-art used alignment algorithm. Even in this simple example, the number of time steps, or steps that the motors had to take to get to the maximum power position, is much less for our knowledge-based technique ($\sim$8 steps) than the standard hill-climbing technique ($\sim$23 steps), which got caught in a local minimum and did not even reach the peak power position. The time steps, in essence, remark on the speed of the automation process. The number of time steps to reach the tracked power level can be seen in Fig. 12.

In the next example, we demonstrate our algorithm improving the performance of the entire array system. A common alignment technique for a fiber array begins by aligning (determining the position for the maximum optical power) in the first fiber, as presented above. The remainder of the fiber array is then rotated around this position, until the maximum power is captured in the last fiber of the array. The rest of the fiber array is then assumed to be aligned. In this example, we show that by aligning

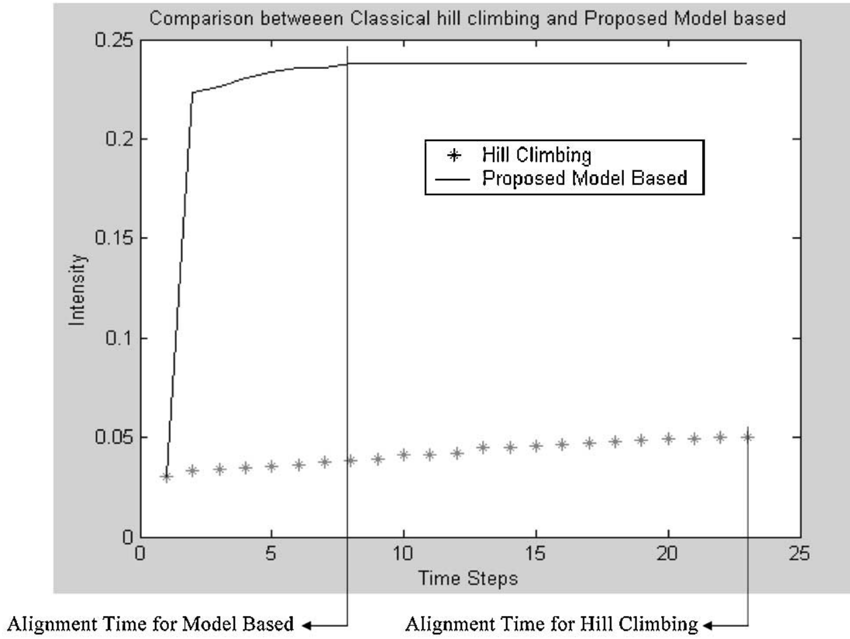

Fig. 12. Iterative time step comparison of out knowledge-based control method versus existing alignment control.

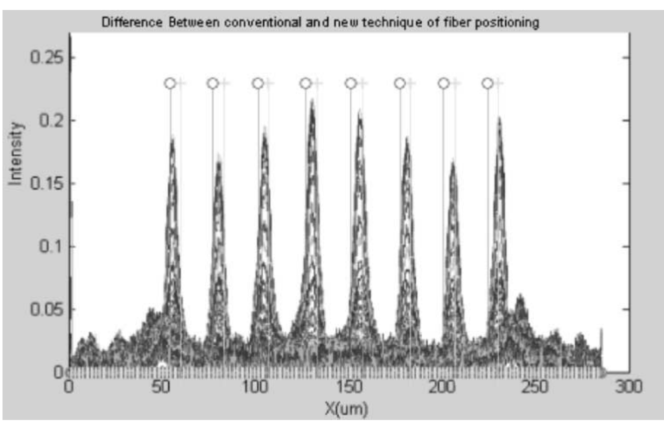

Fig. 13. Fiber array alignment of the hill-climbing algorithm (dark lines and "o" shape) and our knowledge-based control loop (light lines and + shape).

a fiber array using this technique, the overall performance of the system is not considered. In contrast, our knowledge-based control loop takes all of the fibers of the array into consideration and demonstrate an increase in total system performance.

In this example, the total power of the fiber array is calculated by summing the optical intensity at each of the center fiber positions in the array. In the case of the current state-of-the-art technique, if the peak position of the first fiber is caught in a local maximum, as seen in Fig. 11, the total power of all eight fibers is calculated to be 0.1959 (AU). If we allow today's technique the benefit of the doubt that the true optical peak for the first fiber can be found at the global maximum value, the total power calculated for the fiber array is 1.5296 (AU). With our model-based approach, we examine the entire optical field space and determine the position in which a certain alignment will achieve a maximum performance for the entire system. The total power is calculated for the entire state space, and the optimal position of the fiber array is chosen at the point where the alignment gives the best performance for the entire system. In this case, we found a maximum power of 2.0380 (AU), at a position offset from the first fiber center by about 3 μm in the x direction. Comparing our technique verses the industry standard alignment technique, we show an improvement of over 33% when the current algorithm uses the peak maximum of the first fiber and over 940% when the current algorithm method gets caught in the local maximum. In Fig. 13, we show the positioning of each fiber in the array using both the classical technique (centered at the peak power of the first fiber) and our model-based technique. It can be seen that the knowledge-based control loop (denoted by the + shape) is closer to more array peaks than the hill-climbing technique (denoted by the "o" shape).

VI. Conclusion

In this paper, we have introduced a knowledge-based control algorithm for the automation of aligning and packaging optical microsystems. In addition to the current control loop performing a gradient ascent algorithm, we have added MPC, through the use of system simulation. These optical models are accurate and efficient leading to the initial feed-forward set point in the control algorithm. Using this technique, we can increase the speed of the automation process, a critical factor when many components are being packaged at the same time. We also achieve better system performance, as we can easily distinguish the global maximum, instead of the local maximum around the initial starting point. Through these benefits, we reduce the overall cost of the automation process.

The work so far is preliminary, as is our research. We have only verified our algorithms through simulation and are currently starting hardware implementation and testing, with donated equipment from Kulicke & Soffa, Willow Grove, PA. We are also developing advanced optical models that are to be used online in the control loop. Other research include the use of analytical models to help us predict the feed-forward set points through the use of an inverse model and perform curve fitting for the numerical results when analytical models cannot be determined. In addition, the learning loop described in the knowledge-based control is being researched and implemented.

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