PARTS ENTROPY METHODS FOR ROBOTIC ASSEMBLY SYSTEM DESIGN

Arthur C. Sanderson

Department of Electrical and Computer Engineering and The Robotics Institute
Carnegie-Mellon University, Schenley Park, Pittsburgh, Pennsylvania 15213

Abstract

Assembly tasks require the feeding, acquisition, orientation, and mating of parts subject to contact forces. Positional entropy provides an efficient tool for describing an assembly task and its system implementation in terms of the uncertainty in position and orientation of parts as the assembly sequence progresses. A parts entropy measure $H_Q(X)$ may be calculated from the probability distribution of parts positions and orientations at a given assembly step defined over an ensemble of repeated assembly tasks. The part entropy may be reduced mechanically by containerization, fixturing, manipulation, or product redesign. The part entropy may also be reduced using sensors (typically vision or tactile) by reducing the conditional entropy $H_Q(X/Y)$ due to the sensory measurement. The information obtained about part position may be defined in terms of the mutual information I(X;Y). In these terms, the goal of an assembly system is to reduce the joint entropy among parts by mating them in stable configurations. The positional entropy concept provides a unifying tool for assessing the relative effectiveness of systems designs which incorporate both mechanical and sensor-based techniques. The approach may also provide a useful ingredient for quantitative assessment of product designs, complexity of assembly procedures, and flexibility of assembly systems. An example of the use of positional entropy for analysis of an electronic assembly task is given.

1. Introduction

The design of automated assembly systems is increasingly complex due to the evolution of technologies available for manipulation, sensing, and coordination of mechanisms. The design of the parts, choice of the system technologies.implementation of the 'assembly algorithm', and evaluation of performance subject to constraints and priorities are highly interdependent decisions and require systematic methods and procedures. Current approaches emphasize parts sequence design with simulation and queuing analysis to characterize the dynamic, deterministic, flow of parts through a system[1, 2, 3]. The emphasis in these approaches is on cost vs. throughput tradeoffs. This paper introduces a complementary concept and describes the flow of parts in terms of positional uncertainty during the assembly process. In this framework, the assembly system minimizes relative parts entropy by constructing the final assembly. The parts entropy concept provides a tool for comparative analysis of mechanical and sensory technologies through their effect on knowledge of parts position. The approach is probabilistic and leads to measures of assembly complexity and system reliability.

Assembly systems acquire parts, manipulate them, and mate them subject to contact forces (see Fig.1-1). While the mating step itself

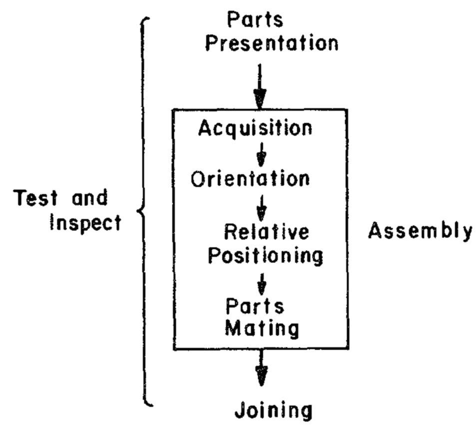

Figure 1-1: Basic steps in the assembly task

provides the focal point for parts sequencing, it is seldom the limiting factor in either system throughput or reliability. In practice, it is the successive handling and positioning of parts from forming or delivery to shipping of the assembly which most often constrains the process. In this sense, assembly may be viewed as a successive convergence of unoriented parts with increasingly precise relative positioning until mating can take place.

The uncertainty of a parts position may be reduced by obtaining information about its position. Such information may be obtained in several ways:

- *Passive mechanical devices* - containers, kits, fixtures, totes, bins, - constrain the position of a part within the known fixed boards.
- *Active mechanical devices* - manipulators, grippers, robots, feeders -- constrain the part position through active mechanical control.
- *Sensory devices* - vision, tactile, proximity, range -- acquire and store position information without mechanically altering the position.

Both passive and active mechanical devices are used routinely in 'hard' automation assembly systems. As programmable devices such as robots have become available, it becomes attractive to program mechanical constraints, although still bounded by the manipulator accuracy. Nonprogrammable positioning prior to robot acquisition is still a major design issue for such systems.

CH2008-1/84/0000/0600$01.00

Sensory devices provide a fundamental alternative to reduce uncertainty through acquiring information rather than reducing possibilities[4, 5, 6]. While such devices are often found to be uneconomical today relative to mechanical fixtures, they offer flexibility and efficient storage of information. Parts entropy provides a basis for comparing the cost of mechanical constraints to that of sensory information in terms of reduction in positional uncertainty. This analysis suggests that while sensory information may be expensive to acquire, it may be cheaper to store, transfer, or alter than mechanical information.

2. Parts Entropy:

One Dimension

Parts entropy will be defined first for a one-dimensional example. Consider a part Q which is dropped randomly into an interval [c,d] of the real axis, Fig.(2-1a). the position of Q will be measured with some accuracy Δ, and therefore there are

$$n = \frac{d-c}{\Delta}, \tag{2.1}$$

possible outcomes of the measurements, $a_1, ..., a_n$. The probabilities of these positions are $P_1, ..., P_n$ such that

$$P_i \geq 0 \ (i=1, ..., n), \sum_{i=1}^{n} P_i = 1. \tag{2.2}$$

The *entropy* of this distribution is given by

$$H_n = H_n(P_1, ..., P_n) = -\sum_{k=1}^{n} P_k \log_2 P_k. \tag{2.3}$$

H_n is commonly used as a measure of 'uncertainty' in the outcome prior to the experiment *or* as a measure of the information obtained from carrying out the experiment. The mathematical properties of H_n and related measures have been studied extensively[7, 8] and will not be described here.

To justify the use of H_n as a parts entropy measure consider two simple examples:

Example 1 - Uniform distribution (Maximum Uncertainty)

$$P_i = \frac{1}{n}, \qquad (i=1, ..., n). \tag{2.4}$$

Then

$$H_Q = H_n = -\sum_{k=1}^{n} \frac{1}{n}\log_2\frac{1}{n} = \log_2 n \text{ bits.} \tag{2.5}$$

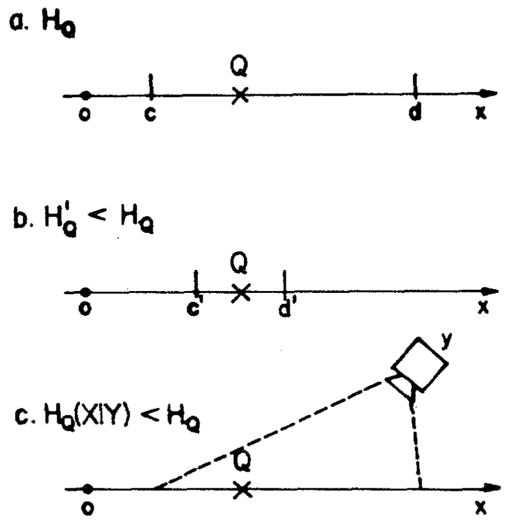

Figure 2-1: Part entropy for one-dimensional example. (a). Position of Q distributed in interval [c,d]. (b). Entropy $H_Q(x)$ is reduced by mechanically constraining Q to [c,' d']. (c). Entropy $H_Q(x|y)$ is reduced by sensing y using a vision system.

$H_Q^{o+1}=0$. This presents several alternatives to the assembly sequence:

- Retain orientation and insert immediately -- requires integration of forming and insertion mechanisms.
- Retain orientation and store -- cost of storing 43 bits as inventory.
- Lose orientation and store -- cost of recovering 43 bits later.

These questions have been the focus of much of the development in automated component handling and insertion equipment. Most commercial automated axial insertion equipment uses the following steps:

1. Tape unformed components and store in rolls.
2. Transfer to tape of sequenced components and store in reels.
3. Form and insert on same machine.

This approach is efficient in retaining stored information, as suggested by the parts entropy sequence in Fig.4-3. However, it requires the additional cost of storing taped and sequenced components. The pre-sequencing of components reduces the flexibility of scheduled tasks as well as the adaptability of a machine to correct errors. These systems typically place restrictions on the role spacings and component spacings on the board, as a consequence of combining forming with mechanically guided insertion.

Other approaches to axial component handling are shown in Fig.4-3. These are:

- *Kitting, K* of formed components (retain orientation and store),
- *Bin-picking, B^4* of formed components, (lose orientation and store),
- *Mechanical Guides, MG* for insertion,
- *Lead visualization, LV^6* for insertion,
- *Visual servoing, VS^6* for insertion.

Example 2 - Singular distribution (Minimum uncertainty)

$$P_i = 1, i = i_o \tag{2.6}$$

$$P_i = 0, i \neq i_o. \tag{2.7}$$

Then

$$H_Q = H_n = -\sum_{k=i_o} \log_2 1 = = 0 \text{ bits.} \tag{2.8}$$

If Q is a part dropped onto a table, its positional uncertainty or entropy (measured over the ensemble of experiments) may be reduces by constraining its position to [c,'d'] (Fig.2-1b) where

$$[d'-c'] < [d- c]\,. \tag{2.9}$$

therefore

$$n' = \frac{d'-c'}{\Delta} < n. \tag{2.10}$$

and the part positional entropy

$$H_Q \propto = -\sum_{k=1}^{n'} \frac{1}{n'}$$

$$\log_2 \frac{1}{n'} < H_Q \tag{2.11}$$

In practice, such constraints are applied by fixtures or mechanical manipulation to constrain part positions.

An alternative to positioning Q mechanically, is to acquire information about Q using sensors. Suppose a vision system observes Q at position $x \in \{a_i\}$ $(i=1, ..., n)$ on [a,b] and computes an estimate of that position $y \in \{b_j\}$, $(j=1,...,m)$, Fig. 2-1c. The set of pairs $\{a_i,b_j\}$ now may be regarded as a joint sample space for the experiment. The joint probability on the joint sample space is $P_{xy}(a_i,b_j)$,

$$P_{xy}(a_i,b_j) \geq 0, \sum_{i=1}^{n} \sum_{j=1}^{m} P_{xy}(a_i,b_j) = 1. \tag{2.12}$$

The joint probability $P_{xy}(a_i,b_j)$ is conveniently written as P(x,y).

In this notation, the conditional probabilities are

$$P(y|x) = P(x,y)/P(x) \tag{2.13}$$

$$P(x|y) = P(x,y)/P(y) \tag{2.14}$$

The information provided by event y about event x is defined by:

$$I(X;Y) = \log \frac{P(x|y)}{P(x)}, \tag{2.15}$$

and the average mutual information over the ensemble is

$$I(X;Y) = \sum_x \sum_y P(x,y) \log \frac{P(x|y)}{P(x)}. \tag{2.16}$$

The average mutual information has the following relationship to the entropy:

$$I(X;Y) = H(X) - H(X|Y), \tag{2.17}$$

$$= H(Y) - H(Y|X), \tag{2.18}$$

$$= H(X) + H(Y) - H(YX). \tag{2.19}$$

In order to apply this result to the vision problem, we need to define the following probabilities:

$$P_x(a_i) = \frac{1}{n}$$

as before.

$$P_{x|y} = \frac{1}{m}, \text{ all j, } |b_j - a_i| \leq \sigma. \tag{2.20}$$

$$m = \frac{2\sigma}{\partial}, \tag{2.21}$$

where σ = range of imaging estimation errors,
∂ = resolution of imaging system.

A uniform distribution of imaging errors has been assumed for simplicity.

From (12)

$$P_{x,y}(a_i,b_j) = \frac{1}{mn}. \quad (2.22)$$

and

$$I(X;Y) = \log_2\left(\frac{n}{m}\right) \text{bits} \quad (2.23)$$

where

$$H(X) = \log_2 n \text{ bits}, \quad (2.24)$$

$$H(X|Y) = \log_2 m \text{ bits}. \quad (2.25)$$

The average mutual information therefore increases with the ratio n/m or in terms of the original constraints, with $|d\text{-}c|/\sigma$. We obtain more information when the imaging error is small relative to the positional uncertainty. The measurement then reduces the part entropy from $H(X) = \log_2 n$ bits to $H(X|Y) = \log_2 m$ bits. Such a visual measurement is therefore the informational equivalent to mechanically reducing the size of the interval form $n\Delta$ to $m\Delta$. The cost of the two strategies could then be compared as a "cost-per-bit" of parts entropy. Either strategy constrains the part to a range for use in the next step, for example, to pick the part up using a manipulator.

3. Parts Entropy:

Three-Dimensions

The positional and orientational uncertainty of a part is closely tied to its geometry and symmetry. The position of a three-dimensional part may be described by a vector $\vec{r} = (x,y,z)$ relative to origin 0. The orientation of the part centered at 0 is most conveniently described by Euler angle rotations. In this case, any general rotation can be described in terms of three successive rotations: angle γ about the z-axis, angle β about the new 0y'-axis, and and angle α about the new 0z"-axis. The set of all possible (α, β, γ) form the rotation group of all possible rotations about the diameters of a sphere.

A part Q suspended in three-dimensions has six degrees - of freedom described by its position coordinates (x,y,z) and its orientation (α,β,γ). Uncertainty in position and orientation may be described by the joint probability distribution $P(x,y,z,\alpha,\beta,\gamma)$ over the joint ensemble. While a large number of relationships may be developed around this distribution, of particular interest is the case when individual degrees-of-freedom are statistically independent:

$$P(x,y,z,\alpha,\beta,\gamma) = P(x)\,P(y)\,P(z)\,P(\alpha)\,P(\beta)\,P(\gamma). \quad (3.1)$$

For this case, the joint entropy of Q is simply:

$$H_Q(q_1, \ldots, q_6) = \sum_{k=1}^{6} H_Q(q_k), \quad (3.2)$$

where q_k is the generalized coordinate $q_1 = x$, $q_2 = y$, etc. $H_Q(q_1, \ldots, q_6)$ is defined as the *part entropy*. For independent degrees-of-freedom, the part entropy is the sum of the entropies over each coordinate of position and orientation. It will be convenient also to consider the contributions to part entropy from position, H_Q^p, and from orientation H_Q^o, since for independence:

$$H_Q = H_Q^p + H_Q^o \quad (3.3)$$

In practice, orientations may be interdependent but independent of position, and vice versa.

For purposes of parts manipulation, the parts entropy is defined with respect to "mechanically distinguishable" positions and orientations. Usually, mechanically distinguishable positions are determined by the resolution δ_i in each coordinate, while mechanically distinguishable orientations are determined by resolution δ_j and symmetry. The symmetry of an object may be most conveniently defined by the set of operations (identity, E, inversion, I, rotation, C, and reflection, σ) which leave the object invariant. The formal description of these operations and their representations is provided by group theory,[9], but will not be introduced here.

Fig. 3-1 shows some examples of orientation parts entropy, H_Q^0, computed for several objects with 10 bits of resolution on each coordinate and uniform probability density functions over the entire range. In this case the sphere has perfect symmetry with respect to orientation and therefore has 0 bits of entropy. As the symmetry of the part decreases, the number of bits required to specify a given orientation increases. An arbitrary solid would require 30 bits . In this sense, H_Q^0 may be used as a measure of part complexity with respect to symmetry properties. Parts with lower H_Q^0 are generally less complex and therefore easier to manipulate and and store. In this discussion, we have considered only rigid parts. Articulated or compliant parts have additional degrees-of-freedom and therefore increase the part entropy. In these cases, degrees-of-freedom may no longer be independent and the joint density of positions and orientations must be defined with care. Other factors which contribute to parts handling complexity such as size, weight, fragility, and accessibility will not be considered in this description of complexity.

3.0.1 Objects on a Flat Surface

In the previous discussion, objects randomly positioned in space were considered. As an object is fixtured, manipulated, or assembled the part entropy decreases as the degrees-of-freedom are constrained. The simplest example of constrained positions is provided by setting the part on a table. In this case, gravity forces the part into one of a set of possible stable positions. The probability density functions then are defined with respect to these stable positions. Consider two examples:

Example 1. *Sphere on a table*

$$H_Q^p = 20 \text{ bits},$$

$$H_Q^0 = 0 \text{ bits},$$

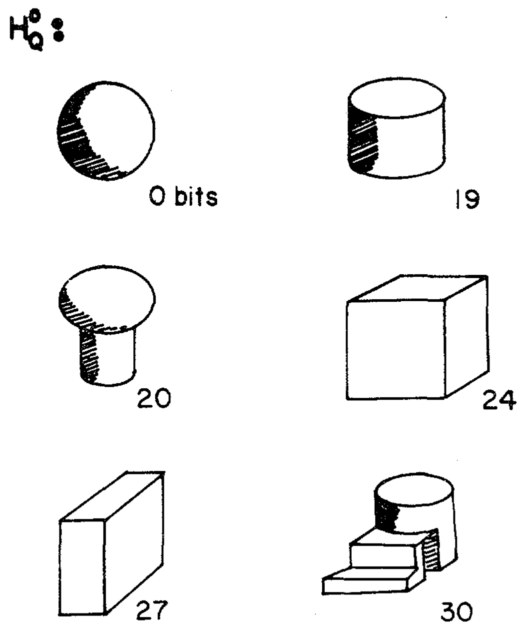

Figure 3-1: Examples of Orientation Parts Entropy for several rigid objects in space.

$$H_Q = 20 \text{ bits.}$$

The entropy of the part is reduced by constraining the vertical position to lie in a plane. Consequently, the complexity of handling the part is also reduced. An interesting extension to this is the sphere in an inverted cone, which has $H_Q = 0$ bits. The inverted cone provides an ideal part fixture by reducing the entropy to 0. It also may accept different sizes of spheres.

Example 2. *Cylinder on a table*

The cylinder has two stable states defined by $\beta = 0^\circ$ (vertical) and $\beta = 90^\circ$ (horizontal). The joint density of orientations is dependent on which state occurs. Thus:

Vertical $\beta v = 0^\circ$

$P(\alpha|\beta = o^\circ)$ = uniform, $0 \leq \alpha 360^\circ$, (symmetry axis)

$P(\gamma|\beta = 0^\circ) = 1$,

$P(z = h/2|\beta = 0^\circ) = 1$, where h is the height,

$P(x|\beta = 0^\circ) = P(y|\beta = 0^\circ)$ = uniform.

Horizontal $\beta_H = 90^\circ$

$P(\alpha|\beta = 90^\circ)$= uniform, $0 \leq \alpha 360^\circ$, (symmetry axis)

$P(\gamma|\beta = 90^\circ)$ = uniform, $0 \leq \alpha 360^\circ$.

$P(z = d/2|\beta = 90^\circ) = 1$, where d is the diameter

$P(x|\beta = 90^\circ) = P(y|\beta = 90^\circ)$ = uniform.

The joint pdf is therefore:

$$P(\alpha, \beta, \gamma, x, y, z) = P(\beta) P(\alpha) P(\gamma|\beta) P(z|\beta) P(x) P(y), \quad (3.4)$$

and the joint entropy is:

$$H_Q = H_Q^p + H_Q(\beta) + H_Q(\alpha|\beta) + H_Q(\gamma|\beta), \quad (3.5)$$

where

$$H_Q^p = 20 \text{ bits}, \quad (3.6)$$

and

$$H_Q^O = H_Q(\beta) + H_Q(\alpha) + P(\beta_v) H_Q(\gamma|\beta_v) + P(\beta_H) H_Q(\gamma|\beta_H), \quad (3.7)$$

$$= H_Q(\beta) + 10 P(\beta_H) \text{ bits.} \quad (3.8)$$

If the cylinder is set down at a random angle and allowed to reach a stable equilibrium, then

$$P(\beta_v) = 1 - P(\beta_H) = \frac{2}{\pi} \tan^{-1}\left(\frac{d}{h}\right). \quad (3.9)$$

Therefore:

$$H_Q^O = -P(\beta_v) \log_2 P(\beta_v) - P(\beta_H) + 10 P(\beta_H). \quad (3.10)$$

A curve showing the dependence of orientational entropy H_Q^O on the shape of the cylinder described by (d/h) is shown in Fig.3-2. The part entropy is greater when the cylinder tends to land on its side, and lower when the cylinder is short and flat (d/h large) since it tends to land on end. As an example, the uncertainty in orientation of a pin dropped on a table is greater than that of a coin (ignoring markings). In terms of orientational complexity, this also suggests that the coin is less complex to position on a flat surface surface than the pin.

4. Part Dependence and Assemblies

Given a set of parts $\{Q_i\}$, $i = 1, ..., N$, the entropy of the set is again defined in terms of the joint probabilities $P[Q_1, ..., Q_N]$, and the parts entropy of the set is the joint entropy $H_Q[Q_1, ..., Q_N]$. If parts are positioned independently, for example, prior to an assembly task, the probabilities will be independent and:

$$P[Q_1, ..., Q_N] = P(Q_1) P(Q_2) ... P(Q_N), \quad (4.1)$$

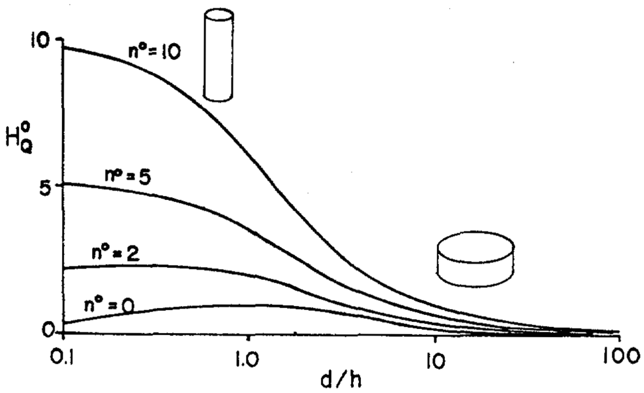

Figure 3-2: Dependence of orientational entropy H_Q^o on cylinder shape d/h for stable orientations on a flat surface. d is the cylinder diameter, and h is the cylinder height.

and

$$H[Q_1, ... Q_N] = \sum_{i=1}^{N} H(Q_i). \tag{4.2}$$

As the assembly task proceeds, individual parts entropies decrease as parts are positioned, and the entropy of the ensemble decreases as part dependence is increased by mating. In this sense, an overall goal of the assembly task is to reduce the entropy of the ensemble of parts. It is convenient to define the entropy of the final (rigid) assembly fixed to the reference frame as $H_Q = 0$, then the relative entropy of parts and subassemblies may be tracked as a function of time during the assembly process. At this point, a parts entropy description may be linked to time-dependent simulation, and the entropy flow in bits/sec described. Alternative system choices and part designs may be compared in terms of entropy flow at different stages of the process. In particular, mechanical versus sensory tradeoffs may be compared in the same framework, and the impact of alternative part designs studied. These relationships can be formalized by considering the more general expansion of the joint density function:

$$P[Q_1, ..., Q_N] = P[(Q_1)] P[Q_2|Q_1] P[Q_3|Q_2Q_1] \ldots P[Q_N|Q_{N-1}, ..., Q_1]. \tag{4.3}$$

and the corresponding entropy over the joint ensemble:

$$H[Q_1, ..., Q_N] = H[Q_1] + H[Q_2|Q_1] + H[Q_3|Q_2Q_1] + ... + H[Q_N|Q_{N-1}, ..., Q_1]. \tag{4.4}$$

Equation (4.4) is a general expression for the total entropy of the assembly.

The value of the total parts entropy in (4.4) changes as the assembly proceeds. Initially the parts are independent as given by (4.2). Consider that parts are mated sequentially $Q_1, ..., Q_N$. First, part Q_1 is positioned and oriented relative to the reference frame, that is, $H[Q_1]$ is reduced. Second, part Q_2 is positioned and oriented relative to Q_1. The resulting conditional entropy

$$H[Q_2 \mid Q_1] \leq H[Q_2] \tag{4.5}$$

reduces $H[Q_1, ..., Q_N]$. The assembly proceeds sequentially, and after assembly step k the total parts entropy is:

$$H[Q_1, ..., Q_N; k] = H[Q_1, ..., Q_k] + \sum_{j=k+1}^{N} H[Q_j]. \tag{4.6}$$

A parts entropy sequence for such a purely sequential process is shown in Fig.4-1. Such a diagram provides a useful picture of the relative entropy reduction and the rate of change as a function of time. Alternative assembly strategies plotted in this fashion may be used for comparative analysis.

4.0.1 Example: Electronics Assembly

The assembly of electronic components into circuit boards is a complex task,[6] and the factors affecting assembly complexity may be expressed in terms of parts entropy:

- Large *variety* of component types and geometries -- Part entropies vary. Variable or adaptive fixtures required for mechanical constraints.
- *Compliant* parts -- Internal part entropies increase total degrees-of-freedom and increase complexity of fixtures.
- *Precision* positioning required -- Final assembly entropy is small.
- *Many parts* per assembly (e.g. 50-100) -- Many contributions to parts entropy.

Several other considerations simplify the assembly task:

- *Planar* assembly -- Board geometry reduces degrees-of-freedom for final placement therefore reduces required entropy.
- *Sequential* assembly -- Part dependence is built into board by conduction paths, thus component insertion may be regarded as purely sequential.

Electronic components may occur in a variety of geometries. Fig.4-2 shows two common examples. The part entropies of these components treated as rigid bodies are:

Unformed Axial:	$H_Q^o = 19$ bits.
Formed Axial:	$H_Q^o = 29$ bits.
Three-lead Planar:	$H_Q^o = 30$ bits.

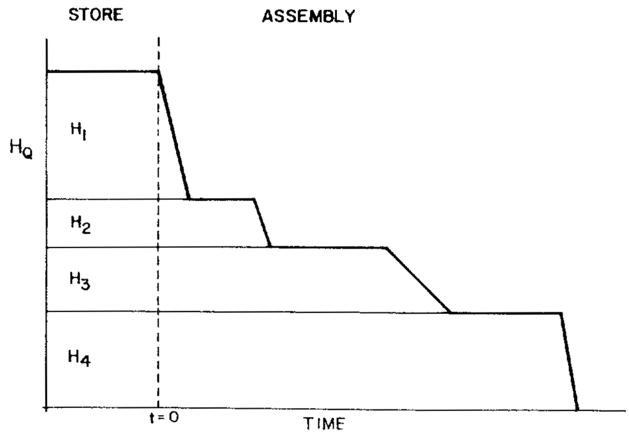

Figure 4-1: Parts entropy sequence for a sequential assembly process in which parts are stored independently and mated to a rigid assembly one by one.

In practice, one must also consider the lead compliance as adding additional degrees-of-freedom to the part. In the case of the formed axial, two important additional degrees-of-freedom are present (if we disregard lead length). These two degrees-of-freedom correspond to relative lead tip axial position Y_{tip} and relative lead tip orientation, Θ_{tip}, with respect to the body. A formed component will not have a uniform distribution of Y_{tip} or Θ_{tip}. Assuming a typical variance of about 10° in lead orientation, one might find internal lead tip entropies of:

$$H^I_Q(Y_{tip}|Q) = 7 \text{ bits},$$

$$H^I_Q(\Theta_{tip}|Q) = 7 \text{ bits}.$$

The resulting total entropy (ignoring lead length) is:

Unformed axial: $H^{o+I}_Q = 33$ bits,

Formed axial: $H^{o+I}_Q = 43$ bits,

Three-lead Planar: $H^{o+I}_Q = 58$ bits.

These considerations of geometry and symmetry suggest that forming of the component as well as addition of compliant leads significantly increase the complexity of the part. When the part is formed, its orientation and lead tip positions are known and therefore $H^{o+I}_Q = 0$. This presents several alternatives to the assembly sequence:

- Retain orientation and insert immediately -- requires integration of forming and insertion mechanisms.
- Retain orientation and store -- cost of storing 43 bits as inventory.

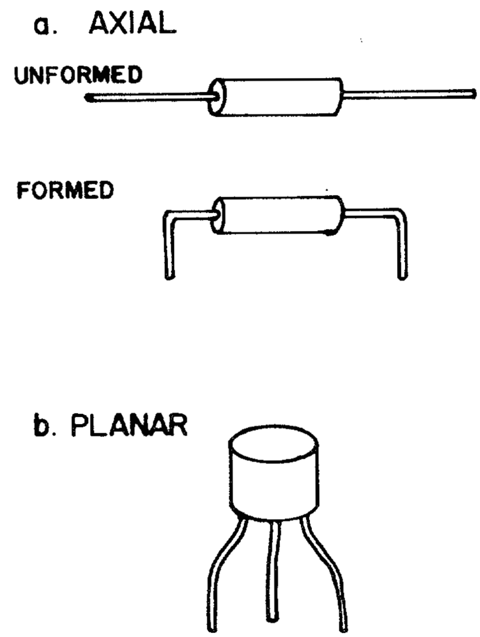

Figure 4-2: Three common examples of electronic component geometries. (a). Unformed axial component, e.g. resistor, and same component formed for insertion. (b). Formed planar component, e.g. transistor.

- Lose orientation and store -- cost of recovering 43 bits later.

These questions have been the focus of much of the development in automated component handling and insertion equipment. Most commercial automated axial insertion equipment uses the following steps:

1. Tape unformed components and store in rolls.
2. Transfer to tape of sequenced components and store in reels.
3. Form and insert on same machine.

This approach is efficient in retaining stored information, as suggested by the parts entropy sequence in Fig.4-3. However, it requires the additional cost of storing taped and sequenced components. The pre-sequencing of components reduces the flexibility of scheduled tasks as well as the adaptability of a machine to correct errors. These systems typically place restrictions on the role spacings and component spacings on the board, as a consequence of combining forming with mechanically guided insertion.

Other approaches to axial component handling are shown in Fig. 7. These are:

- *Kitting, K* of formed components (retain orientation and store),

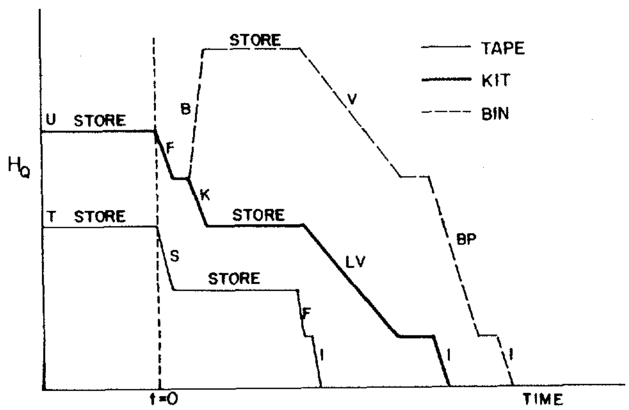

Figure 4-3: Parts entropy sequences for three different electronics assembly strategies:
(1) Taped (T) and Sequenced (S) components, forming (F) and automatic insertion (I),
(2) Formed (F), Kitted (K) components,lead visualization, (LV), and insertion (I)
(3) Formed (F), Binned (B) components, vision (V), bin-picking (BP, and insertion (I).

- *Bin-picking, B*[4] of formed components, (lose orientation and store),
- *Mechanical Guides, MG* for insertion,
- *Lead visualization, LV*[6] for insertion;
- *Visual servoing, VS*[6] for insertion.

We have experimented with various combinations of these approaches[6] in research efforts directed at the design of systems with more flexibility in inventory, component types, and board layout and spacing than is currently available using taped components and insertion machines. Mechanical grippers with adjustable lead guides have been used for acquisition and lead orientation. Multiview lead visualization provides enough accuracy for component insertion using staggered lead lengths. Visual servoing of the lead tips[6] may be used to further reduce tip-to-board conditional entropy for final insertion.

The kitting strategy represented in Fig.4-3 has been incorporated into a production prototype of a flexible component insertion station for axial and radial components (SEAS)[6] developed under a joint research program between CMU and Westinghouse Electric Corporation. The SEAS strategy represents a compromise which avoids preoriented (taped) components, stored sequenced components (kits are random access under program control), and mechanically guided insertions (components are gripped at shoulders of leads, not tops).

The contrast between the taped component strategy and the SEAS strategy in terms of parts entropy may be visualized as follows:

- Taped components:
  - o H_Q^o stored mechanically
  - o $H_Q^o\,(Q_i|Q_j)$, sequence, stored mechanically
  - o H_Q^i stored mechanically by combining forming and insertion mechanisms.
- SEAS strategy
  - o H_Q^o stored mechanically in kit
  - o $H_Q^o\,(Q_i|\,Q_j)$, sequence, stored electronically under program control.
  - o H_Q^i sensed using vision and stored electronically
  - o $H_Q(Y_{tip},\Theta_{tip}|\text{Board})$ sensed directly and reduced under visual servo control.

While it is difficult to assess the relative cost-effectiveness of these strategies, since they are oriented toward different product requirements. The parts entropy formulation provides a common basis to compare the two. The taped component system has clear advantages in system throughput since forming and insertion are combined in one efficient, rigid motion. The SEAS strategy incorporates sensor and electronic storage of information to reduce parts entropy and increases flexibility by removing restrictions on parts storage, component selection, and board layout. The taped component system is commonly used in commercial, large lot-size production. The SEAS ystem is intended for small lot-size production with strict requirements on board size, weight, and reliability.

ACKNOWLEDGMENTS

This work has been supported in part by The Robotics Institute at CMU and in part by a grant from the IBM corporation. Research related to electronics assembly technologies and the SEAS assembly station was supported by the Westinghouse Electric Corporation.

I am grateful to R. Wallace for assistance in preparation of the manuscript.

References

1. Boothroyd, G., "The economics of robot assembly applications,," Tech. Paper ASTIA Doc. AD77-720, RI-SME, November 1977.
2. Nevins, J. L., " Exploratory research in industrial modular assembly," Tech. report R-1276, CSDL Rep., February 1980.
3. Nevins, J. L., D. E. Whitney, and S. C. Graves, " Programmable assembly system research and its application -- A status report," Tech. Paper (MS82-125), RI-SME, 1982.
4. Birk, J, J. Dessimoz, R. Kelley, and R. Ray, "General methods to enable robots with vision to acquire, orient, and transport workpieces,," Tech. report Seventh Rep. Grant DAR 78-27337, Univ. of Rhode Island, Kingston, December 1981.

5. DeFazio, T. L., et al., "Feedback in robotics for assembly and manufacturing," Tech. report R-1563, CSDL Rep., 1983.

6. Sanderson, A. C., and G. Perry, " Sensor-based robotic assembly systems: Research and application in electronics manufacturing," *Proc. IEEE, Special Issue on Robotics,* Vol. 71, July 1983, pp. 856-871.

7. Gallager, Robert G., *Information Theory and Reliable Communication,* John Wiley, New York, 1968.

8. Guiasu, Silvia, *Information Theory with Applications,* McGraw-Hill, New York, 1977.

9. Cracknell, Arthur P., *Applied Group Theory,* Pergamon Press, Oxford, 1968.