2014 IEEE International Conference on Robotics & Automation (ICRA)
Hong Kong Convention and Exhibition Center
May 31 - June 7, 2014. Hong Kong, China

Statistical Identification and Macroscopic Transitional Model between Disorder and Order

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***Abstract*— Food processing provides a lot of possibilities to apply robotics and automation. In this paper, we identify disordered and ordered states of discrete food products. The concept of Degree of Disarray is introduced. Food ordering processes such as vibratory feeders, multi-head weighers, pick and place operations are common automation in food industry to transfer products from a higher to a lower Degree of Disarray. Parts entropy is introduced to describe a product's individual state based on the symmetry categorisation. A macroscopic transitional model is presented which determines a subspace of the disordered arrangement using the eigenvectors of the largest eigenvalues of the covariance matrix. A projection into this created subspace follows. As soon as the disorder state in only one dimension is achieved, the point of disorder can be derived which finally transfers the objects into order. From here, a transformation to any order arrangement in any dimension is possible. This methodology is applied to pick and place operations and experiments are conducted.**

I. INTRODUCTION

At many places in a food production process, previously well ordered products lose orientation and/or positional arrangement and need to be physically re-ordered for the next process. The Food Standards Agency[1] of the United Kingdom says that the food industry accounts for 15% of the UK's total manufacturing sector by value, it is the largest sector of the industry. Within all areas of the food industry, automation has been applied in various ways to either support workers in their area of operation or function at a case-by-case basis [1]–[3]. The motivations and drive forces for such automation are efficiency, consistency of quality, increased hygiene and reduced labour costs [4].

Whereas the motor industry has a robot for every 10 employees, the food industry has a robot installation per 1100 people [5]. British Automation and Robot Association [6] pointed out that robotics have started to make inroads in the food industry [7]. It is expected that this sector will be the next big expansion area [8]. Though most robots in the food industry today are used for handling products packed in primary or secondary packing and palletizing, handling operations are of special interest where a large number of low-skilled personnel are used to transfer unpacked products or feed machines with little added value to the product [9].

In the food industry, there is a large number of food ordering processes such as the vibratory feeder, multi-head weigher, size grader, guidance and buffering conveyor belts, pick-and-place operations [10] and bin picking [11], [12].

In this paper, the research objective is to understand the principle of transferring randomly distributed food products into structure using the Principal Component Analysis (PCA) which was initially introduced by Hotelling [13]. However, a mathematical ansatz [14] can be found earlier by Pearson [15], Cauchy [16] or Jordan [17]. PCA is formalised as a multivariant statistical technique that analyses a list of data arrays and describes these new as a set of orthogonal principal components. In general, the derived variables are inter-correlated. On the one hand, a PCA is applied in order to find the direction of variation, on the other hand, its application aims for data reduction [18]. The last idea is of interest within this paper. Fodor [19] summarised the dimensional reduction techniques and refers to the PCA as the best linear reduction analysis in the mean-square sense [20]. In depth information about its properties, interpretation and analysis can be found in [21].

This paper is organised as follows: The various disorder states of food products are identified statistically in Section II and III. Further, a macroscopic transitional model is presented how to theoretically transfer disordered food products into order (Section IV). Thus, the covariance matrix is analysed and subspaces are created. Locating the centre of disorder, it is possible to re-arrange any ordered formation. On the other hand, decreasing the disorder means that the parts entropy descreases as well. The presented food re-arrangement is then introduced to a pick and place operation in Section V and evaluated.

II. DESCRIPTION OF DISORDERED FOOD PRODUCTS

Mechanisms have a certain Degree of Freedom (DoF) that is the set of independent displacements (x, y, z) and rotations (ϕ, Φ, θ) that specify the displaced or deformed position and orientation of the body or system [22]–[24]. In space, the maximum DoF of an object is six. Food products that are distributed in a three dimensional space ($\Re^3$) or on a planar surface ($\Re^2$) have a certain DoF, too. In order to know the status of disorder, the Degree of Disarray (DoD) is introduced here. This is to describe the initial possible disorder of a food product considering the symmetry and shape and the mathematical space that the objects are arranged in.

Table I summarises all possible DoD states. Two examples are given:

This work was supported by the Engineering and Physical Sciences Research Council (EPSRC) of the United Kingdom under grant number EP/F031394/1. The authors gratefully acknowledge the support from the EC 7th Framework Programme project TOMSY under grant No. 270436.

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[1]Food Standards Agency: www.food.gov.uk, July 2009

TABLE I

IDENTIFICATION OF DISORDER STATES

x, y, z	ϕ, Φ, θ in degrees	Space	DoD
$x,y,z \ \epsilon\Re^*$	$\phi,\Phi,\theta \ \epsilon]0, 2\pi]$	$\Re^3$	6
$x,y,z \ \epsilon\Re^*$	$(\theta = 0 \vee \theta = 2\pi) \wedge (\phi = 0 \vee \phi = 2\pi) \wedge (\Phi = 0 \vee \Phi = 2\pi)$	$\Re^3$	3
$z = 0 \wedge x,y \ \epsilon\Re^*$	$(\phi = 0 \vee \phi = 2\pi) \wedge \theta,\Phi \ \epsilon]0, 2\pi]$	$\Re^{2.5}$	4
$z = 0 \wedge x,y \ \epsilon\Re^*$	$(\theta = 0 \vee \theta = 2\pi) \wedge (\phi = 0 \vee \phi = 2\pi) \wedge (\Phi = 0 \vee \Phi = 2\pi)$	$\Re^{2.5}$	2
$z = 0 \wedge x,y \ \epsilon\Re^*$	$(\phi = 0 \vee \phi = 2\pi) \wedge (\Phi = 0 \vee \Phi = 2\pi) \wedge \theta \ \epsilon]0, 2\pi]$	$\Re^2$	3
$z = 0 \wedge x,y \ \epsilon\Re^*$	$(\theta = 0 \vee \theta = 2\pi) \wedge (\phi = 0 \vee \phi = 2\pi) \wedge (\Phi = 0 \vee \Phi = 2\pi)$	$\Re^2$	2
$z = y = 0 \wedge x \ \epsilon\Re^*$	$(\phi = 0 \vee \phi = 2\pi) \wedge \theta,\Phi \ \epsilon]0, 2\pi]$	$\Re^{1.5}$	3
$z = y = 0 \wedge x \ \epsilon\Re^*$	$(\theta = 0 \vee \theta = 2\pi) \wedge (\phi = 0 \vee \phi = 2\pi) \wedge (\Phi = 0 \vee \Phi = 2\pi)$	$\Re^{1.5}$	1
$z = y = 0 \wedge x \ \epsilon\Re^*$	$(\theta = 0 \vee \theta = 2\pi) \wedge (\phi = 0 \vee \phi = 2\pi) \wedge (\Phi = 0 \vee \Phi = 2\pi)$	$\Re^1$	1

1) In some cases, food products are transported from one plant to another in bins ($\Re^3$). Disordered products then need to be relocated and reoriented (6 DoD) for further processing. Depending on the symmetry of the products (see Table II), the rotation can be neglected. Hence, only a translation is necessary to put them into a structured arrangement (3 DoD).
2) Within food companies, products usually move along a conveyor belt, on a planar, two dimensional surface. The DoD should be three (two translational and one rotational DoF about the z-axis). However, another rotational DoD has to be added since food products on a conveyor belt can be upside down, for instance (see space $\Re^{2.5}$).

III. INTRINSIC RELATION BETWEEN SYMMETRY AND PARTS ENTROPY

As mentioned before, a food product F has t DoD, where $t = 6$ in a three dimensional space. We assume that they are statistically independent and can be written as:

$$P_F(x, y, z, \phi, \Phi, \theta) = P_F(x)P_F(y)P_F(z)P_F(\phi)P_F(\Phi)P_F(\theta) \tag{1}$$

This describes the uncertainty of position and orientation of a single food product. The next step is to introduce entropy in order to understand the connection to disorder and apply this statistical approach.

In this paper, the entropy is interpreted as a measurement of a mean information content or information density, as it was defined by Shannon primarily [27]. The information content indicates the statistical significance of a signal. This will be the minimal amount of bits that are necessary for a transmission or demonstration of an information. This is calculated as follows:

$$I(x_r) = log_2 \frac{1}{P(x_r)} = -log_2 P(x_r) \tag{2}$$

where

$$P(x_r) \geqslant 0 \, (r = 1, ..., n), \sum_{r=1}^{n} P(x_r) = 1 \tag{3}$$

x_r is a symbol from a discrete alphabet $X = x_1, x_2, ..., x_s$. n is the number of symbols of the alphabet X. $P(x_r)$ is the probability that the source will choose x_r from X. This is greater, the more improbable a symbol will be. The information content does not have a huge impact technically but the mean information. This is the point entropy becomes relevant because the mean information content or the entropy is defined as:

$$H(x) = -\sum_{r=1}^{s} P(x_r) log_2 P(x_r) \tag{4}$$

Taking this into consideration and applying to Equation 1, the entropy for a food product is as follows:

$$H_F(d_1, ..., d_6) = \sum_{h=1}^{3} H_{\mathrm{F}}^{\mathrm{P}}(d_h) + \sum_{k=4}^{6} H_{\mathrm{F}}^{\mathrm{O}}(d_k) \tag{5}$$

where d_h describes the already known positional and orientational coordinates ($d_1 = x$, $d_2 = y$, etc.). Sanderson [28] defines this as the parts entropy.

Instead of describing the shape of the product [26], the number of planes of symmetry and their relationship is considered here (Table II). Following this approach also provides information about the location of the Centre of Gravity (CoG) of a product which is useful for further processes including gripping, for instance. If a product is of uniform density, the intersection of these planes of symmetry locates the CoG. On the other hand, the intersection of two or more planes of symmetry forms a line. In this case, the CoG is described by the symmetry line. Using a resolution of v bits for each transitional and rotational parameter, the parts entropy for a food product is determined in Table III.

TABLE II

CATEGORISATION OF SHAPE [25], [26]

Symmetry
no planes
1 plane
2 plane
3 planes
∞ planes, 1 axis
∞ planes and axis

TABLE III

ORIENTATIONAL PARTS ENTROPY CONSIDERING SYMMETRY

Symmetry	3D Disarray	2D Disarray	1D Disarray
0 planes	$3v$	v	0
1 plane	$3v$	v	0
2 plane	$3v-1$	$v-1 \vee v$	0
3 planes	$3v-3$	$v-1 \vee v$	0
∞ planes, 1 axis	$2v-1$	$v-1 \vee v$	0
∞ planes and axis	0	0	0

IV. Macroscopic Transition between Disorder and Order

Whereas parts entropy gives individual information about discrete food products, this section derives a macroscopic transfer function for the transition between disorder and order (see Fig. 1). The idea is to reduce the dimension of disorder stepwise until a disordered arrangement is achieved in only one dimension. This means that the maximum DoD in $\Re^3$ is reduced to two translational and one rotational DoD as shown in Table I. In $\Re^1$, the transitional DoD is along a line. Once this stage is achieved, it is possible to determine the point of disorder and transfer disorder into order. From $1\mathrm{D}_{\mathrm{Order}}$, ordered arrangements in any dimension is achievable.
This section determines the covariance matrix for randomly distributed objects in $\Re^p$, where $p = 2, 3$. Its eigenvalues are taken as principal components to create a new vector space $\Re^q$, where $q = p - 1$. A projection onto the new disarray plane and disarray axis respectively finalises the stepwise reduction of the parts entropy.

A. Creating an Euclidean Subspace using Principal Components

Discrete food products are randomly distributed in an Euclidean space $\Re^p$, where $p = 3$. Their location $\vec{f}_{i,3\mathrm{D}}$, $i = 1, ..., N$, are summarised in the following matrix:

$$\mathbf{F}_{\mathrm{Disorder,3D}} = \begin{pmatrix} f_{x1,3\mathrm{D}} & \cdots & f_{xN,3\mathrm{D}} \\ f_{y1,3\mathrm{D}} & \cdots & f_{yN,3\mathrm{D}} \\ f_{z1,3\mathrm{D}} & \cdots & f_{zN,3\mathrm{D}} \end{pmatrix} \quad (6)$$

Using a statistical approach, this data can be newly structured. The aim is to reduce the amount of components, which is equivalent to a transformation that reduces the dimension. Principal components are extracted which are linear combinations of the original data. Thus, the covariance matrix and its eigenvectors need to be determined.
The arithmetic mean for the x-, y- and z-component of the matrix $\mathbf{F}_{\mathrm{Disorder,3D}}$ can be calculated:

$$\vec{\bar{f}}_{3\mathrm{D}} = \begin{pmatrix} \bar{f}_{xi} \\ \bar{f}_{yi} \\ \bar{f}_{zi} \end{pmatrix} = \begin{pmatrix} \frac{1}{N}\sum\limits_{i=1}^{N} f_{xi,3\mathrm{D}} \\ \frac{1}{N}\sum\limits_{i=1}^{N} f_{yi,3\mathrm{D}} \\ \frac{1}{N}\sum\limits_{i=1}^{N} f_{zi,3\mathrm{D}} \end{pmatrix} \quad (7)$$

Equation 7 is used to identify the covariance matrix:

$$\Sigma_{3\mathrm{D}} = \frac{1}{N}\sum_{i=1}^{N}(\vec{\bar{f}}_{3\mathrm{D}} - \vec{f}_{i,3\mathrm{D}})(\vec{f}_{i,3\mathrm{D}} - \vec{\bar{f}}_{3\mathrm{D}})^{\mathrm{T}} \quad (8)$$

Equation 8 is a symmetric matrix, so $\Sigma_{3\mathrm{D}} = \Sigma_{3\mathrm{D}}^{\mathrm{T}}$. The Schur decomposition is to separate Equation 8 into an orthogonal matrix $\mathbf{Q}_{3\mathrm{D}}$ and a diagonal matrix $\Lambda_{3\mathrm{D}}$, so that

$$\mathbf{Q}_{3\mathrm{D}}^{'}\Sigma_{3\mathrm{D}}\mathbf{Q}_{3\mathrm{D}} = \Lambda_{3\mathrm{D}} = \mathrm{diag}\left(\lambda_{1,3\mathrm{D}}, ..., \lambda_{p,3\mathrm{D}}\right). \quad (9)$$

Here, $\lambda_{j,3\mathrm{D}}$ for $j = 1, ..., p$ are the eigenvalues of the covariance matrix $\Sigma_{3\mathrm{D}}$ and $\mathbf{Q}_{3\mathrm{D}}$ contains the equivalent eigenvectors $\vec{q}_{j,3\mathrm{D}}$. The two eigenvectors of the two largest eigenvalues are used to generate an orthogonal subspace $S_{2\mathrm{D}}$. Figure 2 shows the the Euclidean subspace and the randomly distributed food products. So the equation of the new subspace $S_{2\mathrm{D}}$ is:

$$S_{2\mathrm{D}} = \vec{\bar{f}}_{3\mathrm{D}} + \mathcal{L}(\vec{q}_{j,3\mathrm{D}}) \,\mathrm{with}\, j = [1, ..., p] \backslash j_{min(\lambda_{j,3\mathrm{D}})} \quad (10)$$

Below, the linear hull $\mathcal{L}(\vec{q}_{j,3\mathrm{D}}) = \mathcal{L}(\mathbf{S}_{2\mathrm{D}})$ to simplify the notation. The reason for choosing the eigenvector of the largest eigenvalue is that these vectors build a subspace that minimises the Euclidean distance between the original 3D point cloud and maximises the variance of the projections. The orthogonal mapping will be described in the following section.

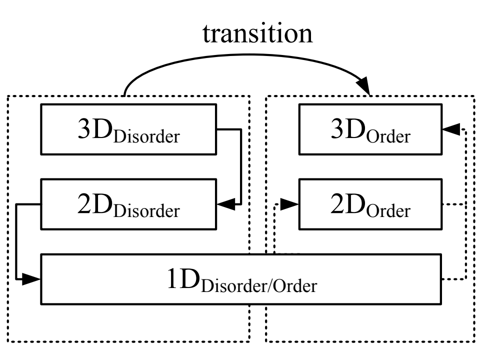


Fig. 1. Global transition between disorder and order

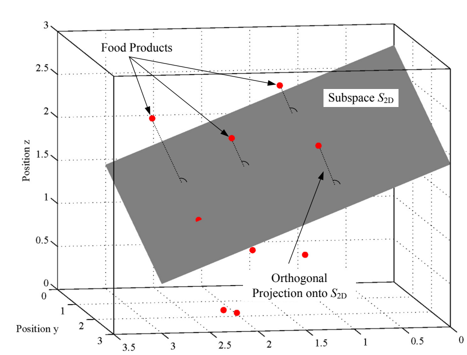


Fig. 2. 3D distributed products (red) and orthogonal Euclidean subspace (gray) using eigenvectors of the covariance matrix

B. Mapping Disordered Point Cloud to Subspace

Equation 10 describes the subspace of two dimensions. The food products that are located in $\Re^3$ with a minimal Euclidean distance to this plane $S_{2\text{D}}$ are now projected orthogonally into this subspace using Geometric Algebra. There are two conditions that need to be met:

1) The vectors $\left(\vec{f}_{i,3\text{D}} - \vec{f}_{i,2\text{D}}\right)$ - its absolute value is the Euclidean distance - should be perpendicular to $S_{2\text{D}}$, so

$$\mathbf{S}_{2\text{D}}^{\text{T}} \left(\vec{f}_{i,3\text{D}} - \vec{f}_{i,2\text{D}}\right) = 0, \tag{11}$$

where $\vec{f}_{i,2\text{D}}$ is the projected point of $\vec{f}_{i,3\text{D}}$.

2) The new projected point $\vec{f}_{i,2\text{D}}$ should be located in the subspace $S_{2\text{D}}$. Thus, it is a linear combination like

$$\vec{f}_{i,2\text{D}} = \vec{\overline{f}}_{3\text{D}} + \mathbf{S}_{2\text{D}}\mathbf{L}, \text{ where } \mathbf{L} = \begin{pmatrix} l_1 \\ l_2 \end{pmatrix}. \tag{12}$$

l_1 and l_2 are unknown variables.

Equation 15 will provide two and Equation 16 three equations. Thus, it is possible to solve the two conditions with five unknowns in total. Finally, the food products that were randomly distributed in a three dimensional space are now reduced into a two dimensional space. The new positions of the products are

$$\mathbf{F}_{\text{Disorder},2\text{D}} = \begin{pmatrix} f_{xi,2\text{D}} \\ f_{yi,2\text{D}} \\ f_{zi,2\text{D}} \end{pmatrix} \tag{13}$$

C. Determination of the Line of Disorder

Having reduced the initial point cloud into an Euclidean plane and applying the methodology of Section IV-A, a covariance matrix $\Sigma_{2\text{D}}$ can be determined for the two dimensional point cloud $\mathbf{F}_{\text{Disorder},2\text{D}}$. Its eigenvalues are $\lambda_{k,2\text{D}}$ for $k = 1, ..., p$ and the eigenvectors are $\mathbf{Q}_{2\text{D}}$, respectively. The arithmetic mean of $\mathbf{F}_{\text{Disorder},2\text{D}}$ is $\vec{\overline{f}}_{2\text{D}}$.

The linear subspace $S_{1\text{D}}$ can now be written as a combination of the arithmetic mean and the largest principal component. Thus, everything will add up to:

$$S_{1\text{D}} = \vec{\overline{f}}_{2\text{D}} + \mathcal{L}(\vec{q}_{k,2\text{D}}) \text{ with } k = k_{max(\lambda_{k,2\text{D}})} \tag{14}$$

Equation 14 describes a line in the subspace $S_{2\text{D}}$, so that each point of $\mathbf{F}_{\text{Disorder},2\text{D}}$ has the minimal Euclidean distance to this new subspace $S_{1\text{D}}$. Figure 3 shows an orthogonal top view onto $S_{2\text{D}}$ of Figure 2. The food products are already projected onto the two dimensional subspace. The linear subspace $S_{1\text{D}}$ is plotted. However the projection onto this line of disarray can be described as follows:

Equivalent to the 3D to 2D disorder reduction, $\mathcal{L}(\vec{q}_{k,2\text{D}}) = \mathcal{L}(\mathbf{S}_{1\text{D}})$. This is to simplify the notation. In order to determine the orthogonal projection, Equation 15 and 16 need to be adjusted to:

1) The vectors $\left(\vec{f}_{i,2\text{D}} - \vec{f}_{i,1\text{D}}\right)$ should be orthogonal to $S_{1\text{D}}$, so

$$\mathbf{S}_{1\text{D}}^{\text{T}} \left(\vec{f}_{i,2\text{D}} - \vec{f}_{i,1\text{D}}\right) = 0, \tag{15}$$

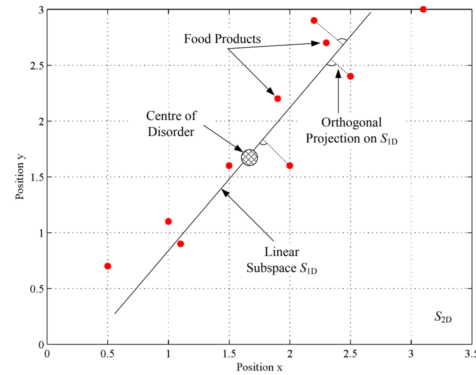


Fig. 3. 2D distributed products (red) and linear subspace (gray) using largest principal component

where $\vec{f}_{i,1\text{D}}$ is the projected point of $\vec{f}_{i,2\text{D}}$.

2) The new projected point $\vec{f}_{i,1\text{D}}$ should be a linear combination of

$$\vec{f}_{i,1\text{D}} = \vec{\overline{f}}_{2\text{D}} + m\mathbf{S}_{1\text{D}}. \tag{16}$$

m is an unknown variable.

Solving these four equation, $\vec{f}_{i,1\text{D}}$ can be determined. Thus, the centre of disorder will be $\vec{\overline{f}}_{1\text{D}}$ as it can be seen in Figure 3. The difference $\left|\vec{f}_{i,1\text{D}} - \vec{\overline{f}}_{1\text{D}}\right|$ will be the absolute distance between the centre of disorder and each food product along one principal component.

D. Transformation into Order Arrangements from 1D Disorder

The two previous sections showed how to determine $\vec{f}_{i,2\text{D}}$, $\vec{f}_{i,1\text{D}}$ and finally the centre of disorder $\vec{\overline{f}}_{1\text{D}}$ from three dimensional disarray. The centre of disorder is equivalent to the centre of order as it can be seen in Figure 1. This stage allows to arrange the food products into any ordered structure as required using the transformation matrix $\mathbf{T}_{\text{Order}}$:

$$\mathbf{T}_{\text{Order}} = \begin{pmatrix} \mathbf{R}_{\text{EUL}}(\phi, \Phi, \Theta) & \vec{t} \end{pmatrix} \tag{17}$$

E. Reducing the Parts Entropy

Whereas the macroscopic transitional model describes the global re-arrangement of the food products, this has an impact on the individual DoD as well. As mentioned before, Table III links the symmetry category to the parts entropy. The lower the dimension of the space considered, the lower is the parts entropy. Thus, by transferring objects that are distributed in a three dimensional space to spaces of lower dimensions, the parts entropy and therefore the DoD will decrease. In the status of $1\text{D}_{\text{Disorder}}$, the orientational parts entropy is zero. Here is the link to 1D_{Order} and other possible structured arrangements.

V. Experimental Results for Pick and Place Operations

Delta robots have been designed for high-speed pick and place tasks that are capable of around 150 picks per minute. This type of robot has typically a 1-2 kg payload. The pick

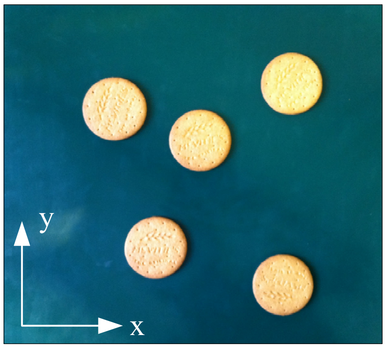


Fig. 4. Planar biscuits randomly distributed on a conveyor belt

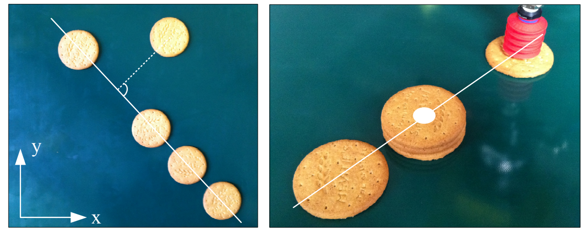
and place system is typically fed by conveyor belts. A vision system will determine the position and orientation of the food product. The robot picks the product up from the conveyor, brings the product into the desired orientation, and places it on the target location.
This product transfer operation for ordering food products is used as an example for the developed transitional model. In this case, the operation concentrates on ordering products from $2\mathrm{D}_{\mathrm{Disorder}}$ to $1\mathrm{D}_{\mathrm{Disorder}}$.

A. Typical Input-Output Arrangements

As mentioned, the input of pick and place operations is usually on planar surfaces. While products are transported on conveyor belts, they are handled at the same time. The order sometimes gets lost during further processing and products have to be re-arranged on the same conveyor belts. Figure 4 shows a typical arrangement where planar biscuits (one symmetry axis, ∞ planes) are randomly distributed. In this case the conveyor belt moves in y-direction with a constant velocity. The flow and density of the food products is almost uniform.
Figure 5 shows different containers for cookies. Before biscuits get packaged, these layouts or similar arrangements are preferred in food industry. The biscuits for the container in Figure 5(b) for instance need to be ordered in a row of four equally spaced cookies. Here, each row has multiple layers. This is a common output structure of a food ordering process.

(a) Cookie Arrangement (b) Biscuit Plastic Container

Fig. 5. Examples of cookie containers for packaging



(a) $S_{1\mathrm{D}}$ Line of Disorder (b) Centre of Disorder/Order

Fig. 6. Stepwise reduction of disorder on a conveyor belt

B. Line and Centre of Disorder for Groups of Products

On the one hand, each biscuit can be transferred to a new area into an ordered arrangement. By doing so, each product is picked up, directly transferred into the structured arrangement and into the container respectively. This assignment is optimised by the transition model presented in this paper. The arrangement into order is taken place on the same area of the conveyor belt. Therefore, the constant flow of biscuits is divided into groups of a certain amount of products. This is dependant on the output structure.
In Figure 6, a group of five cookies is given as an example. A line of disorder $S_{1\mathrm{D}}$ is determined according to the statistical analysis in Section IV-C. Thus, each of the five food products have a minimal Euclidean distance to this subspace. Considering an equally spaced distance between the biscuits, these are transferred onto the line of disorder for the final output arrangement.
Figure 6(b) shows an alternative array. The products are stacked layer by layer having determined the centre of disorder. Having finished this food ordering process, the bunch of products will be picked and placed into the suitable container.

C. Experimental Simulation and Evaluation

We have simulated a pick and place operation where $N = 5$ products scattered on a planar surface are ordered along a line using the proposed PCA approach. The eigenvector of the largest eigenvalue of the covariance matrix gives the minimal distance between the food products and the vector according to Equation 14. The products are projected and equally positioned along this line. Then, the group is picked and placed in the final position. Figure 7 shows the simulation results. The simulation is repeated 100 times and the total cost of handling recorded. The mean cost of the global transitional model is 37.61.

VI. Conclusions

This paper investigated a macroscopic transitional model from disorder to order. Here, we specifically looked at ordering processes in food industry. The different disorder states have been identified. On a microscopic level, the disorder of individual food products is determined introducing parts entropy. It shows that the Degree of Disarray and the parts entropy of an individual discrete food product decrease as the dimensional space is reduced. Thus, the global mathematical

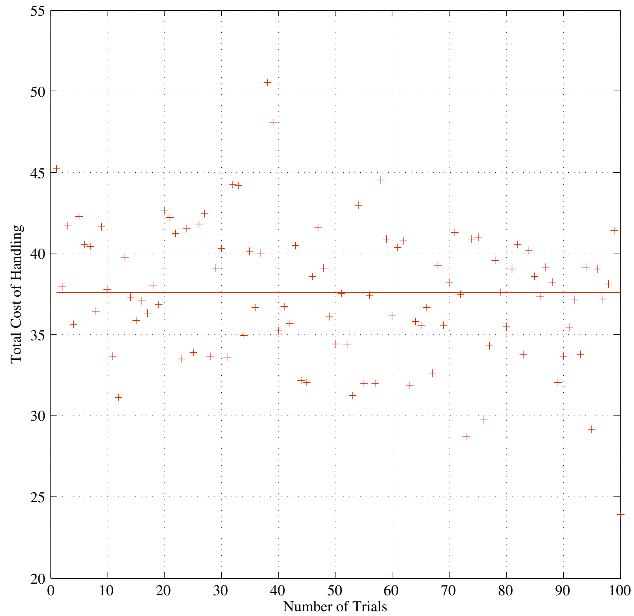


Fig. 7. Simulation of the PCA algorithm for 100 pick and place trials

model presented is to reduce the Euclidean space and project the position of the objects into this subspace: The location of food products are assumed as a point cloud. This random distribution is then analysed in a statistical way using the eigenvectors of the covariance matrix. A linear combination of a lower dimensional subspace is formed and the point cloud projected into this subspace. This procedure is followed until the centre of disorder is found. Using a linear transformation matrix, the food products can be transferred into any structured arrangement.

In food industry, there are practical ordering operations that show where this implemented approach has advantages over commonly used operational processes. In pick and place operations for instance, the transitional model presented allows structuring randomly distributed food products on a plane surface handling a group of products. This ordering operation is processed with respect of the disordered location. Instead of picking each object and placing it in the container, this macroscopic model re-arranges the foodstuffs and then transfers the grouped, ordered food products into a suitable container or onto another conveyor belt for further processing. In future work, we will compare the proposed technique to other optimisation algorithms such as the Hungarian algorithm or Travelling Salesman Problem.

ACKNOWLEDGMENT

The authors would like to thank Dr. Graham Purnell from the University Centre Grimsby and Mr. John Reed from Silsoe Technology.

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