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Intelligent Injection Curing of Bacon

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Abstract

Much of the meat we enjoy to eat, undergoes a curing process for preservation, tenderizing, flavoring, and presentation purposes. Curing on an industrial scale is commonly done by injecting brine, a solution of salt and other ingredients, into the meat. Current methods rely on manual control of process settings. Natural variations, between and within meat pieces, are ignored resulting in sub-optimal dosing and distribution of brine. Were the process parameters instead to be adapted to the individual meat piece and the specific area, yield and quality could be improved. This paper reports research to investigate the fundamental aspects of the injection process, constructs a process model for existing machines and proposes a self-calibrating controller based on Reinforcement Learning. A vision based robotic injection system is presented for experimentation with the injection process, with the specific purpose of determining the potential for adapting process parameters to the natural variation in the meat pieces.

Keywords: Robotic injection; Process modeling; Reinforcement learning; Food manufacturing

1. Introduction

Many of our favorite meat products are subject to a curing process, where salt and other ingredients such as; phosphate, nitrate, sugar, and flavoring, are added to the meat [1]. Salt as the central ingredient, has the effect of increasing the solubility of proteins and thereby improving meat’s ability to retain water. However, if the concentra-

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Fig. 1. industrial injection of; (left) backs (British bacon); (right) bellies (American bacon).

tion of salt gets too high, muscle fibers begin to shrink and proteins risk getting washed out [2]. The allowed brine or salt content will be determined by the customers or by legislation. Workers continuously monitor the gain and adjust the process parameters accordingly by weighing either an entire batch or random samples before and after processing. Ideally, the salt should be uniformly distributed throughout the meat, as close to the wanted concentration as possible.

Salt can be administered in the form of salt crystals externally or as brine, a solution of salt etc., either externally by submersion, or internally by injection. Salt applied externally will slowly penetrate and diffuse into the meat, through chemical processes. Salt is able to diffuse 2-$7\times10^{-10}m^2/s$ depending on the temperature [3]. Because of the amount of time required for salt to diffuse over longer distances, injection with a dense pattern is often preferred in industrial food production. Industrial injection curing of meat is done using a battery of needles as seen in Figure 1. The main process parameters; injection speed and pressure, are adjusted to achieve the wanted salt content/weight gain across a batch of meat. Many meat products are not uniform, they will usually consist of a combination of different muscles and other types of tissue that each absorb brine differently. Current injection machines are unable to adapt to this kind of variation, with sub-optimal results as a consequence. Additional process steps may be put to use, before or after brine injection, to improve the result. This typically involves mechanically treating the products to improve brine absorption and diffusion. However, if the results of the injection itself could be improved additional process steps could be omitted.

1.1. Contribution

Initially the authors have sought to understand central aspects of the injection process through a number of basic experiments. Based on these, a model of the injection process is created and a self-calibrating injection controller for "chip-tuning" existing machines is proposed.

This is followed by an investigation of the possibilities for using machine vision to add more intelligence and adaptability to the injection process. Specifically, beginning to look into the options for predicting and adapting the injection parameters to variation in the individual meat pieces. To facilitate these experiments, a vision based robotic injection system is constructed.

2. Related work

Increasingly intelligent and adaptive robotic systems are required for further automation of the food industry, where natural variation poses the main challenge. For use cases where the variation is manageable, the combination of a 3D vision system and an industrial robot is proving successful. This has been demonstrated with a lab-scale robotic pick and place solution for large pieces of meat [4]. The system employs real-time sensing to provide the path planning algorithm with up to date information about the position and orientation of the products that are to be moved. Similar systems are becoming commercially available [11]. Other areas outside of the food industry have similar challenges, where vision is a central part of the solution. One example is seen in [5], where an automated robotic surface coating system is shown to adapt to changing surfaces by relying on 3D vision.

When problems cannot be fully understood or get too complex, people have turned to data driven models and Reinforcement Learning (RL). In [6], the problem of making a controller for acrobatic low speed helicopter flight is solved by learning a model of the system and finding the optimal control policies using RL. The model is created using supervised learning on data logged during piloted flight. Using RL, policies are learned through interaction with this model, before being successfully applied to the real helicopter. In [7], a self-learning and self-improving laser welding system is proposed that does not require an engineered model of the welding process. Some of the complexity involved in laser welding includes: temperature, humidity, thickness and contamination. These variable are tackled by an actor-critic RL algorithm, which learns to apply the appropriate welding power from rewards. The rewards are given based on the distance between the desired welding depth and the achieved welding depth. Automating the processing of meat possesses similar hard to model complexity that RL might help overcome. However, in prior work such as [6], the complex control problems were solvable because the problems had been simplified using on domain knowledge. Specifically, the complex problem of helicopter control was condensed into only a few parameters that are known to be central to the control of helicopters. In other areas with less well defined problems, these parameters may be difficult to determine by hand, making the problem unmanageable using classic RL. However, with recent advances RL, it has been shown that complex control problems such as controlling a 24-DoF humanoid model are solvable [8].

3. Initial experiments

To answer fundamental questions and to gather the data needed for creating the first simple predictive model of the injection process, initial experiments have been conducted. The amount of data in these experiments is quite limited and the conclusions are thus only preliminary. The experiments all involve injecting pork backs with a range of different injection parameters. The brine solution consists of 65.5% water, 9.9% salt, 6.9% nitrate salt, 2.3% phosphate and 15.3% dextrose. This is a standard solution and under normal circumstances the wanted gain in the product would be around 15%, by weight, resulting in a salt content of around 2.2%.

3.1. Computed tomography for inspecting brine distribution

Computed Tomography (CT) were used to get an idea of the distribution and diffusion of the brine and to get very accurate 3D models for comparing the volume of the meat pieces prior to and after injection. It is evident from the CT slices in Figure 2 that the brine is not uniformly distributed and the volume has noticeably increased.

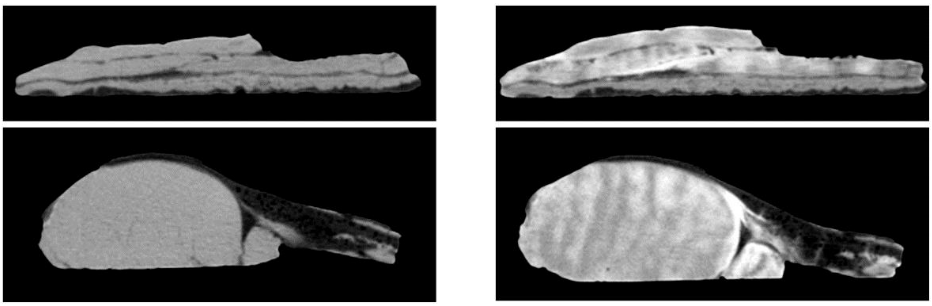

Fig. 2. Computed Tomography scans; (left) prior to brine injection; (right) post brine injection.

3.2. Effects of injection speed and pressure

The industrial injection machine seen in Figure 1 (left), was used to inject six pieces of meat with a range of parameters covering the parameter space. The two parameters that can be adjusted are brine pressure (bar) and speed (rpm), corresponding to the number of injections per minute. Figure 3 (left), shows the gain in weight with a fixed speed of 50 rpm and varying pressure. Figure 3 (right), shows the gain using a constant pressure of 1.3 bar with varying speeds.

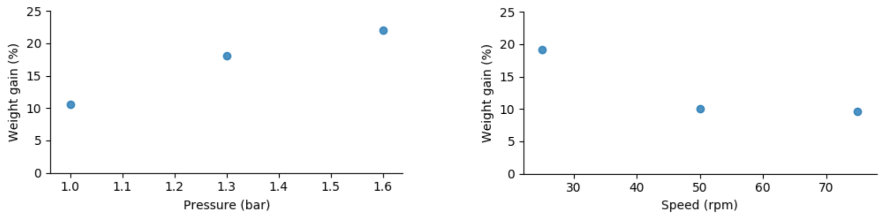

Fig. 3. Gain in weight given; (left) constant speed, varying pressure; (right) constant pressure, varying speed.

Intuitively, gains diminish with the amount of brine being injected, since the meat's capacity for absorbing brine gets saturated. The pressure vs. weight plot in Figure 3 (left), seems to follow this hypothesis by approximating an upper limit increasing exponential decay. Injection speed vs. weight, seen in Figure 3 (right), also follow the hypothesis by resembling a lower limit decreasing exponential decay as the needles spend less time in the meat.

3.3. Self-calibrating injection controllers

A new controller should replace the workers who are adjusting the parameters of injection machines throughout the day. The parameters must be adjusted over time because of many, difficult to model, effects that influence the injection result. Some of these effects include variation in; temperature, brine, meat, and blockage of needles. All of these and more can correlate with a slow drift or sudden changes in the response to the injection parameters. Some of the information that a controller could take into account is listed in Table 1. A controller based on RL would be able to learn control policies for existing injection machines, where even medium and long-term effects could be taken into consideration.

Table 1. state space

Parameters	Range	Resolution
Type	[0,..,10]	1
Weight (kg)	[3.0,..,9.0]	0.1
Recent performance	[-1.0,..,1.0]	0.01

With basis in the measurements shown in Figure 3, a multi-variable 3rd order polynomial regression model is created. The limited amount of data results in a rough model that can be used for developing a self-calibrating controller. Figure 4 shows the models gain response across a valid range of pressures and speeds.

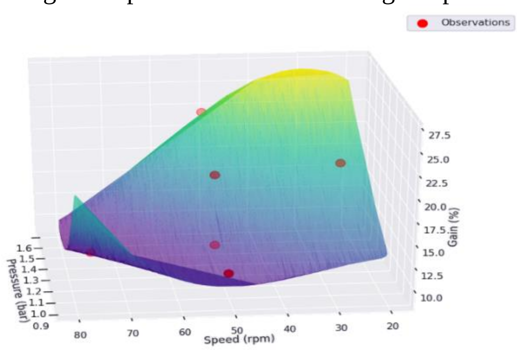

Fig. 4. regression model response for a range of valid process parameters

The regression model is wrapped in OpenAI's gym framework [9] and the Proximal Policy Optimization RL algorithm, which is known for its stability and ease in training [8], is used to learn control policies through interaction with the model. The action space is listed in Table 2.

Table 2. action space

Parameters	Range	Resolution
Speed (rpm)	[0,..,100]	1
Pressure (bar)	[0,..,2]	0.01

We propose two reward functions; a lenient reward function where the agent is rewarded in proportion to how close it gets to the goal gain seen in Equation 1, and a stricter reward function where the agent receives no reward if the goal is exceeded as seen in Equation 2.

$$\text{Eq. 1. } \mathrm{R}_{lenient}(\mathrm{S},\mathrm{a}) = \begin{cases} \frac{goal}{gain}, & gain > goal \\ \frac{gain}{goal}, & otherwise \end{cases} \qquad \text{Eq. 2. } \mathrm{R}_{strict}(\mathrm{S},\mathrm{a}) = \begin{cases} 0, & gain > goal \\ \frac{gain}{goal}, & otherwise \end{cases}$$

Figure 5 shows the frequency of outcomes for the two different reward strategies. This is to been seen as a barebones demonstration of a controller based on RL, with amble opportunity for adding additional information to the state space and complexity to the action space.

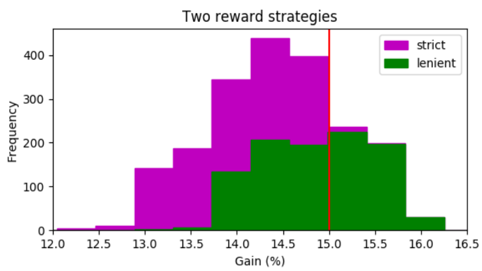

Fig. 5. stacked frequency of outcomes from learned control policies' interaction with regression model.

3.4. Vision-based gain measurement

Prior to the advent of industrial injection machines, brine was injected by hand. The butcher could use his expertise to decide where and how much to inject. Injection machines, on the other hand, process all areas the same way. A noticeable consequence of this is that bones must be removed prior to injection. With complex products that consist of a combination of different muscles and tissues, each with different absorption properties, it results in an uneven distribution of brine. If gain could be measured locally, it could reveal a variation in brine absorption and open for new possibilities in adapting the injection parameters to individual areas in a piece of meat. First it must be determined whether a correlation between weight gain and volume gain exists. Three pieces of meat are weighted as well as scanned in a CT scanner before and after being injected. A hand held injection needle, not much different from what can be found in private kitchens, was used to carefully inject the meat without the violent mechanical treatment and the resulting deformation from industrial injection machines. A gain measure based on volume is computed from the convex hull of 3D models produced from the CT scans. This should be comparable to the global weight measure that is obtained by weighting the meat. The resulting gain from the two measurement methods is shown in Figure 6.

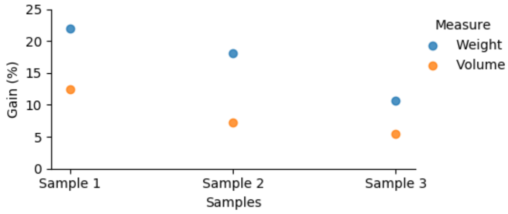

Fig. 6. relationship between gain in weight and gain in volume.

The two measures look to be correlated but a significant offset exists. Part of this can be explained by the difference in density between meat and brine, but the majority will have to be explained by error sources. These include; inaccuracies in the volume calculation, air pockets inside the meat being filled.

4. Robotic injection

The investigation, into the possibilities for using machine vision to add more intelligence to the injection process, begins with the construction of a robotic injection system consisting of a LBR IIWA 14 R820 collaborative robot, a Kinect for Windows RGB-D camera, and a custom made brine injection system driven by air pressure. The camera is used to locate and measure the meat as well as the table surface. This is necessary in order to avoid injecting outside of the meat or into the table. Before opening the valve to the pressurized brine, the needle is inserted 1 cm into the meat, this insures that only limited amounts of brine ends up outside of the meat. The needle is then moved into the meat until it reaches 1 cm above the table and the valve is closed again before the needle is retracted. The software is build using the Robot Operating System (ROS) [10].

4.1. Measuring local variation

Figure 7 shows a representation of the resulting local volume gain from the robotic injection of brine. The map is generated by computing the height difference between a point cloud captured before the injection and a point cloud of the injected meat. This change can be translated to a gain caused by the injection with a specific set of injection parameters.

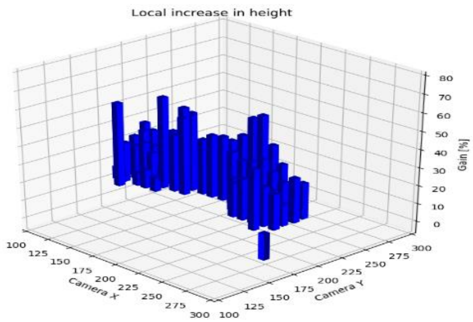

Fig. 7. map of local change in height (%).

The local variation in the individual meat pieces is evident from Figure 7, which shows significant variation in the local gain resulting from injection with a fixed set of parameters. Whether this variation can be predicted from appearance features is going to be investigated going forward, by extracting features from local image patches using autoencoders. Initial results from the autoencoder's ability to represent different image patches can be seen in Figure 8.

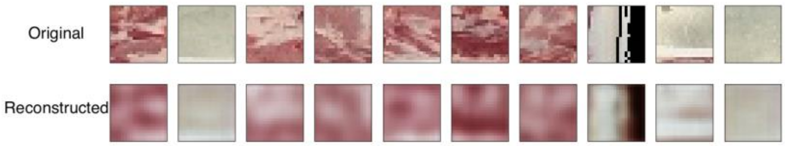

Fig. 8. sampled image patches vs. decoded latent representations from autoencoder.

Furthermore, by applying Principal Component Analysis to the latent representations of image patches, the ability to group areas based on their similarity in appearance is shown in Figure 9.

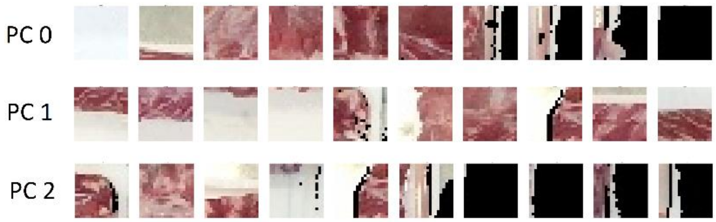

Fig. 9. representable samples from the range of the top 3 principal components.

5. Discussion

The initial model of the injection process is not expected to be a precise representation of the process. With the limited amount of data and difficulty in modeling variables, such as the structure of the meat and erratic leaks, this is not possible. However, with each subsequent injection experiment, more data will be gathered and the model will be refined. With sufficient data and the appropriate type of problem, RL looks like a promising direction to investigate when building controllers that can cope with many influencing factors and complex processes such as brine injection in meat. RL opens up for plenty of opportunities for adding complexity in both state space and action space. Going forward, the data collected using the robotic injection setup will be used for modeling the complex injection process at the level of individual injections.

Determining change in mass locally and in a non-invasive manner, as opposed to a global weight, brings several benefits and challenges. We have only begun to determine if the challenges can be overcome and the necessary data can be extracted from the noisy environment.

Acknowledgements

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