A Machine Learning Approach to Drought Stress Level Classification of Tobacco Plants

C. Stocker[1], F. Uhrmann[1], O. Scholz[1], C. Hügel[1], T. Rademacher[2], M. Siebers[3], U. Schmid[3]
[1]Fraunhofer Institute for Integrated Circuits IIS, Erlangen, Germany
{stockech, Franz.Uhrmann, Oliver.Scholz}@iis.fraunhofer.de
[2]Fraunhofer Institute for Molecular Biology and Applied Ecology IME, Aachen, Germany
[3]University of Bamberg, Cognitive Systems Group, Bamberg, Germany
{michael.siebers, ute.schmid }@uni-bamberg.de

Abstract

We show that a model for drought stress level classification of tobacco leaves can be learned from measurement data. The data was acquired using a sheet-of-light measurement system developed at the *Fraunhofer Institute for Integrated Circuits IIS*. Spatial attributes like length, width or bending were extracted by fitting a parameterized leaf model to the measurement data. The attributes were transformed to simple attribute vectors describing relevant aspects of plant growth and stress evidence. The resulting attribute vectors were used to train decision trees, neural networks and linear regression classifiers. To provide a broad range of data, plants were assessed in a planned measurement campaign. Stress was induced by cutting off the water supply to simulate drought. Evidence for drought stress could be recognized from the data. Classification of whole plants yielded better results than classification of single leaves.

1 Introduction

A highly controlled production of plants in greenhouses or phytotrons (e.g. automated production of plants for pharmaceutical applications or high-throughput plant phenotyping for breeding) requires fully automated systems for the continuous monitoring of the growth conditions and the plant status. While simple factors like climate, nutrition and water supply can be controlled with simple reactive systems, more complex aspects like the detection of stress, diseases or pest infestation require intelligent systems which are able to detect anomalies in plant growth. To accomplish this, a measuring system must be designed which is able to capture the necessary features of plant growth in a non-destructive manner. Furthermore, a classification model is required which provides information about how to assess the measurement data.

The aim of our work was to evaluate whether it is possible to construct such a classification model directly from measurement data without additional expert knowledge. As part of its internal funding program the Fraunhofer Future Foundation is currently promoting the Malaria-Vaccines project of the *Fraunhofer IME*, Aachen. Through the participation of two additional Fraunhofer Institutes (IPT and IIS) the project synergistically combines expertise from the life sciences, engineering and medical technology fields. One of the major project goals is to develop an automated production facility for the GMP-compliant manufacturing of IMEs novel malaria vaccine candidates in tobacco plants. The task for our work was to model the behavior of tobacco plants when exposed to drought stress. From a machine learning point of view, this is a classification task of distinguishing stressed plants from regularly watered plants. Drought was chosen as the stress type of interest since it is easy to simulate by cutting off irrigation. In a measurement campaign designed for this work, a set of tobacco plants was measured over the course of one week. To trigger drought stress, the plants were cut off from water supply according to a fixed time schedule. Plant data was acquired using a sheet-of-light measurement system developed at the IIS in the *Department for Contactless Test and Measuring Systems*.

Furthermore, a biologist was asked to assess the plants' stress level according to the measurement data. These ratings served as classification labels for supervised machine learning techniques. The measurement data was reduced to attribute vectors describing essential features of the physical shape of a plant. This was done using a parameterized leaf model developed at the *Fraunhofer IIS*.

Combined with the labels provided by the expert rating, these attribute vectors form an input data which is compatible with standard machine learning techniques. Decision trees, neural networks and linear regression were used for classification to evaluate which technique is suited best for the data provided.

2 Acquisition of plant data

2.1 Measurement campaign setup

The data used for this work was acquired in a measurement campaign carried out at the IME. Over the course of one week, tobacco plants of different stress states were measured on a regular basis. The test group consisted of 50 Nicotiana tabacum plants grown hydroponically in stonewool blocks. They were sowed in five groups of ten plants in a weekly sequence. The plants were cultivated in a phytotron under LED light in a nutrient film technique (NFT) system at 25°C during the light phase (16h) and 22°C during the dark phase (8h) with a constant relative humidity of 70%. During the light phase, the plants in the gullies were periodically supplied with nutrient solution (15 min flow / 45 min off). The measurements were started when the last group reached an age of three weeks. Thus the plants ranged in three to seven weeks of age at the beginning of the measurements. Each day, all plants were measured two times. The first measurement was carried out in the morning, the second one in the afternoon.

To accomplish objective states of drought stress, single plants were cut off from water supply at fixed points in time during the measurement campaign. At each cut-off point, two more plants of each age group were exposed to drought stress. Once a plant was separated from irrigation, it was kept unwatered until the measurement campaign was finished. The exact water cut-off points were distributed over the week in such a way that every three measurements, two more plants were cut off from irrigation. Since there were 14 measurements, this scheme was set off by one measurement to define objective start and end points. This means that at the first measurement no plant was exposed to drought stress to acquire an unstressed measurement of each plant individual as a reference point for further changes over the course of the following measurements. At the last measurement, there was no additional cut-off point included to keep two watered plants as a reference with respect to the stressed individuals.

2.2 Measurement system

The measurements were carried out using a sheet-of-light measuring system developed at the *Fraunhofer IIS*. This system projects laser light onto the plant, which is then captured by several cameras. The cameras are positioned below, above and in front of the plant. In the measuring process, the plant is turned about 360 degrees to expose all plant parts to the cameras. During the rotation, the distance from the plant to the camera is measured by tracking the positions of the points were the laser light was reflected on the plant's surface. The result is a 3D point cloud of the plant surface. An example for the result is given in figure 1.

Figure 1: Picture of a 52 days old tobacco plant (left side) and the corresponding 3D reconstruction (right side). Each leaf is shown in a different color.

2.3 A parametric leaf model

Since most conventional machine learning algorithms require data in the form of attribute vectors, the 3D point clouds were further processed to acquire relevant aspects of plant growth in the form of attribute-value pairs. Each attribute stands for a certain spatial feature of a leaf, e.g. the length, the width, the bending angle towards the ground or its widthwise bending. Figure 2 illustrates one of the bending attributes.

The attribute extraction was done in two steps. In the first step, the plant was segmented into leaves using a spatial clustering algorithm. In the second step, attribute extraction was done using a leaf model fitting algorithm. In the course of this algorithm, a model leaf is transformed until it fits the segmented leaf. From the resulting transformation the values of the attribute vector can be calculated. Further details of the attribute extraction methods can be found in [Uhrmann *et al.*, 2013]. An example of the result can be seen in figure 3.

Figure 2: Example showing the default model with no bending (left side) and a model with a slight bend towards the ground (right side).

Figure 3: The result of the model fitting algorithm. Each leaf (shown in different colors) has a model leaf fitted to it.

2.4 Expert ratings

A biologist rated the stress level of the measured plants to create class labels for supervised classification algorithms from human expert knowledge. To avoid external influences the ratings were performed in a controlled experiment situation. The expert was asked to assign stress classes to each plant measurement. The classes were *no stress*, *moderate stress* and *strong stress*. This simple 3-choice distinction was chosen to keep the ratings comparable and as objective as possible. A more complex scale, for instance an estimation of stress measured in days of exposure, would suffer from personal rating preferences of the expert.

For each measurement the expert was presented a side view photo of the plant. The expert was asked to rate each of the 700 measurements. To conceal the pattern to which the plants were stressed during the measurements, the plant images were shown in a random order. Additionally, the age of the plant in days was provided to the expert. The resulting class labels were assigned to the corresponding leaf attribute vectors by extending each vector by a class attribute whose value was the classification of the respective plant.

3 Classification of tobacco leaves

3.1 Preprocessing

Processing the raw measurement data to attribute vectors describing the leaf shape consists of three steps: Plant measuring and reconstruction, leaf segmentation, and model fitting. Each of these processing steps may induce noise into the data, which is described in the following.

1. In the measuring and reconstruction step it can happen that parts of a leaf cannot be captured. The main reason

for this are occlusions, e.g. upper leaves that cover up parts of lower leaves and prevent the laser beams from reaching all parts of the plant surface. This might result in gaps or clipped leaves which is challenging for the following processing steps.

2. In the segmentation step there is a possibility that a leaf is not recognized, e.g. because it is to close to another one. In that case, the resulting leaf mesh would contain two leaves. This is problematic because the model fitting algorithm is designed for an input mesh which contains only one single leaf. The opposite might also be the case: More than one leaf is detected where there should be only a single one. This might happen if there are big gaps in the point cloud, which virtually split the leaf into several parts. The resulting meshes would contain parts of a single leaf, which are all assumed to be whole leaves. Both effects add noise into the data since the model fitting algorithm is not able to detect inconsistent input meshes.

3. In the model fitting step, the major source for errors is invalid input data from the previous processing steps. An example for this is given in figure 4. The point cloud data of the small leaf in the front contains gaps, which causes the model fit to fail. The resulting attribute vector for this leaf will therefore contain errors and reduce the quality of the classification.

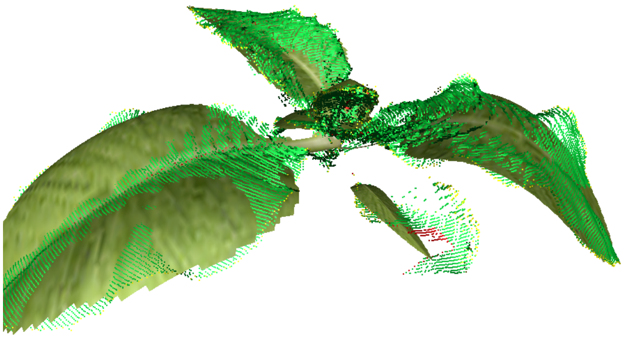

Figure 4: An example for an invalid model fit. The small leaf in the front was not fitted correctly due to gaps in the point cloud data.

Avoiding these errors in advance is difficult. The pivot is the measuring and reconstruction step, because errors in this step propagate through all subsequent steps. However, measuring and reconstruction of plants is very challenging. Due to the complex shape of plants there is no way to avoid occlusions in all cases. Therefore it is probably impossible to design reconstruction algorithms which are able to avoid gaps and clippings completely.

Consequently, data cleaning is required to filter out erroneous attribute vectors before classification. In the course of our work, two types of cleaning were applied to the data.

Firstly, the distance between the model leaf and the original point cloud was taken as an error indicator. This was measured as the accumulated distance between each point of the model leaf mesh and the nearest point of the reconstructed leaf mesh. Each attribute vector which showed a very large distance value was deleted from the data.

Secondly, each attribute vector was checked for inconsistent values with respect to correlated attributes. As an example, figure 5 shows a plot of all leaf attribute vectors, showing the leaf length on the x-axis and leaf area on the y-axis. There is a correlation between the scale and the area of a leaf. All leaf attribute vectors which exceeded a fixed threshold with respect to the ratio between leaf length and area were considered as outliers. The failed model fit in figure 4 is a typical example for how this outliers emerge. In that case, the model leaf was deformed to a needle-like shape. Therefore the ratio between scale and area is too small and the attribute vector can easily be identified as an outlier.

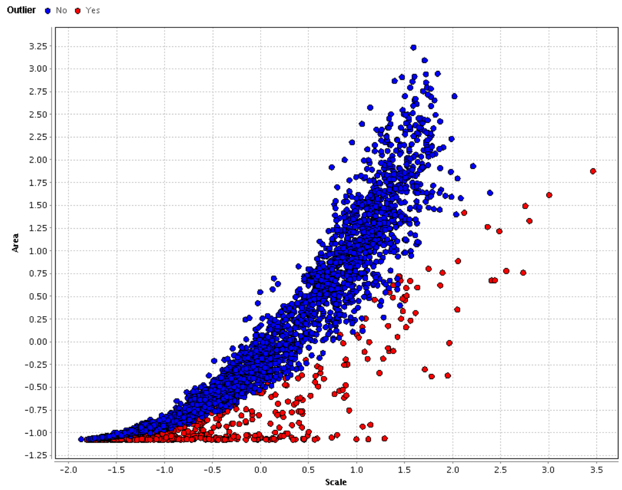

Figure 5: The correlation between the area and the length (scale) of a leaf. Outliers are marked in red.

3.2 Classification and evaluation

Decision trees, neural networks and linear regression were used for classification to evaluate which of these classifiers is suited best for the data. We used RapidMiner 5.3 for the data mining. Each classifier was tested using cross-validation with three subsets of validation. The input data was weighted by stratification, since healthy plants outnumbered moderately and strongly stressed plants.

Different approaches to learning have been tested, which differed in two aspects.

Firstly, the approaches differed in the number of classification classes. Tertiary classification approaches included the classes *healthy*, *moderately stressed* and *strongly stressed*. Moreover, binary classification approaches were tested, in which the class *moderately stressed* was omitted.

Secondly, the approaches used different input data. Approaches on leaf level were based on the attribute vectors corresponding to the respective leaves. On plant level, some adaptations were required, since no global plant attributes were provided by the preprocessing steps. Therefore the attribute vectors of single leaves were transformed to attribute vectors describing whole plants. This was done by creating plant attributes containing the mean values of all corresponding leaf attributes. Furthermore, global plant attributes were calculated, e.g. height, radius and the total leaf surface area.

Regarding all aspects, there are four different approaches which were carried out. For each approach, the already mentioned classifiers were applied. Therefore 12 classification results were achieved. Table 6 shows the respective accuracy rates.

The first approach was performed using leaf attribute vectors as input data and performing a tertiary classification. The best accuracy rate was 52.04% using linear re-

	tertiary, leaves	binary, leaves	tertiary, plants	binary, plants
decision tree	43.77%	52.28%	75.07%	93.69%
neural network	45.40%	72.02%	82.46%	97.08%
linear regression	52.04%	81.81%	82.35%	95.53%

Figure 6: The results of the classification, showing the accuracy rates for each learning approach.

gression. However, this poor result is reasonable. As it was explained in section 2.4, leaf attribute vectors were labeled with the rating of the whole plant. However, tobacco leaves show different behavior when exposed to drought stress, depending on the type of the leaf. A tobacco plant tries to retain young, strong leaves as long as possible. Consequently, older leaves show stress symptoms earlier than younger leaves. Since the leaf data was labeled with the ratings of the whole plant, the poor result of the first approach can therefore be explained because of discrepancies between the labels and the data.

The second approach was carried out by performing binary classification on the leaf attribute vectors. The reason was to assure that stress is recognizable in the leaf data at all. If the intermediate class is omitted, there is more tolerance for the definition of class boundaries, which allows for an easier classification. This second approach yielded much better results. Accuracy rates up to 81.81% could be reached using linear regression. Consequently stress symptoms can be recognized from the data, but the labels provided are not suitable for tertiary classification on the leaf level.

In the third approach tertiary classification was performed on the level of whole plants, which yielded much better results. An accuracy rate of 82.35% could be reached, using linear regression. Since this was a tertiary classification, this is a considerable improvement compared to the first and second approach. Furthermore this confirms that the stress state of a plant cannot be classified by considering single leaves only.

The fourth approach was a binary classification on the plant level. Is was carried out to check whether the binary classification yields considerably better results compared to the tertiary classification. The task was almost solved by neural networks, with an accuracy rate of 97.08%. Consequently, tertiary classification is more challenging than binary classification. One of the possible reasons for this is explained in section 4.

It is worth to note that decision trees performed worse than any other classifier in all approaches. This indicates that decision trees seem to have a learning bias which is disadvantageous for the classification of this kind of data. This might be due to the fact that the input data contains only continuous values.

4 Discussion and Outlook

Since our work in this field is still in progress, there are plenty of open points and ways to proceed. In order to further increase accuracy rates, some effort must be put into the reduction of errors in the preprocessing steps, since they are propagated through all subsequent processing steps and are difficult to be recognized in the cleaning step.

Furthermore, other approaches to extract plant attributes from the measurement data might yield different results than our model fit approach. For example, Lin et al. [2013] use a simple function model describing the shape of the leaf margins. It is possible that such an approach to leaf modeling might also provide suitable data for classification tasks.

Moreover, there are also different ways in which the transition from leaf to plant level classification could be realized. In our approach, plants were mainly classified based on the mean values of the corresponding leaf attributes. Another possible approach would be to perform pre-classification on the leaf level, and a second classification on the plant level. This might yield better results since not every leaf of a plant would be considered individually, whereas the smoothing effects of calculating mean values is avoided.

Another critical point is the reliability of the expert ratings. As it was stated in section 2.4, the classification labels stem from interviewing a human expert. These ratings might vary in precision due to the subjectivity of human judgments. As our fourth classification approach showed, adding an intermediate class between healthy and stressed plants adds plenty of complexity to the classification task. If this is due to vague intermediate classifications by the expert, a machine learner which is trained with this data might therefore never be able to yield optimal results.

Consequently the reliability of the expert ratings must be validated. A possible approach would be to repeat the ratings with the same data but different experts. If the ratings match, this is an indication that human experts are reliably able to distinguish stressed from healthy plants.

5 Related work

As far as we are aware, there is only little related work in the field of stress classification of plants by machine learning methods. In [Wu *et al.*, 2007], a leaf recognition algorithm is described using probabilistic neural networks based on leaf images acquired by scanner or digital cameras. Such an approach might be adapted to distinguish stressed from healthy plants.

In [Chaerle and Van Der Straeten, 2001], a survey of several techniques for monitoring plant health is provided, including fluorescence imaging, thermal imaging and others. These methods have the benefit that stress can be detected earlier than with visual measurement systems since visible changes in plant shape are already effects of biochemical processes, which can be detected earlier with the described methods. Therefore it would be worth to apply machine learning techniques on the data provided by these methods and compare the results with our work.

However, some of this methods are not applicable with our framework since high throughput of single plants must be assured. For instance, systems based on hyperspectral imaging, like they are used in [Römer *et al.*, 2012], are not feasible in our context although they have successfully been applied in the detection of drought stress.

6 Summary

We have shown that constructing a model for the impact of drought stress on plant growth can be inferred from measured geometric leaf features using machine learning techniques. These features are acquired using a sheet-of-light measurement system. Such a system could be used to monitor plant growth in greenhouses, as they are used in the production of pharmaceutical products.

To build our model, we set up a measurement campaign to acquire a broad range of data, extracted attributes of interest from the spatial data and applied several machine learning techniques to achieve a number of comparable results. In this measurement campaign, tobacco plants of the species *Nicotiana tabacum* were measured on a regular basis and stressed according to a fixed schedule. Drought was chosen as the stress type of interest since it is easy to simulate by cutting off irrigation. The measurement data was reduced to vectors of attribute-value-pairs describing essential features of the physical shape of a plant. This was done using a parameterized leaf model developed at the *Fraunhofer IIS*. Combined with labels provided by expert ratings, these attribute vectors form input data which is compatible with standard machine learning techniques.

Classification on the level of single leaves yields poor results (lowest accuracy: 43.77%) because the labels were not appropriate for single leaf data. However, classification on the level of whole plants yields good results with accuracy rates up to 97.08%.

There are several ways to further increase classification performance. For instance, further effort could be put into the reduction of errors in the preprocessing step. Using different data sources or using other methods for the transition from leaf to plant level might also yield better results.

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