can be treated in a uniform way throughout the different system stages.

Hence, the presented extension of fuzzy classifiers allows an explicit treatment of trustworthiness at runtime, although it is fairly simple and easy to compute. The approach presented here basically acts similar to a gradual dynamic selection of the most trustworthy input signals. It is thus easy to understand as well as to engineer. And what is more, with the proposed approach, the uncertainty is handled in the most general way which is easy to integrate into a fuzzy classifier. This contributes to our idea of a system wide and easy to engineer trust management in (complex) embedded systems.

6. Conclusion

To summarize, this paper has introduced a concept for extending rule based fuzzy classifiers in order to deal explicitly with dynamic uncertainties at runtime. It is independent of specific kinds of membership functions and inference methods. It hence can be used as an addition to existing fuzzy classifier methods. Its simplicity allows an easy understanding of its effect in order to keep the classification system transparent. The degree of certainty of the classification result expresses the uncertainty implied in the classifier itself as well as the dynamic uncertainty of the current feature vector. Thus it fits well into the trust management framework, where the trustworthiness of the output can be processed further. This enables a trustworthy operation for critical applications because misclassifications are avoided as far as possible and the trustworthiness of a made classification decision can be judged. Nevertheless, the approach is simple, easy to handle and fast to engineer.

In future work we will take a more detailed look at uncertainty induced by the training process. E.g., more detailed information about conflicting rules will be incorporated into the trust level of a result and thus be a valuable contribution towards a overall trustworthy classification.

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