An adaptive image processing system based on incremental learning for industrial applications

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***Abstract*—Machine learning has been applied in image processing system for object recognition, inspection and measurement. It assumes that the provided training objects are representative enough to the real objects. However in real application, new (unlearned) objects always emerge over time, which may deviate from the trained (learned) objects. The conventional image processing system using machine learning is not able to learn and then recognize these new objects.**

In this paper, an incremental learning based image processing system is presented. The overall system consists of three layers: execution, learning and user. The conventional image processing system is constructed in execution layer. In learning layer, adviser and incremental learning are applied to generate a new classifier. The incremental learning is differentiated into different methodologies: data accumulation and ensemble learning. Through the adviser, a proper methodology can be recommended. User is able to interact with the system via user layer. Comparing to the conventional image processing system, the proposed system is robust in industrial applications, since it deals with the classification problems dynamically.

Keywords—adaptive image processing, industrial image processing, machine learning, incremental learning

I. INTRODUCTION AND STATE OF THE ART

Machine learning has been widely applied in image processing system for industrial applications, such as automated recognition, inspection and measurement. It has become a nature component of the conventional image processing system. For example, support vector machine is used in [1] to classify defective LCD (liquid crystal display), while in [2] to classify the defective potatoes on a conveyer. In [3], three different machine learning methods are used for image region classification: decision tree (using C4.5), concept description (AQ18), and back propagation algorithm. In [4] a bayesian network classifier is used to recognize the graphic symbol. Besides the standard machine learning techniques, there are lots of literatures about the varieties of machine learning. Kotsiantis and his colleagues provided a detailed comparison of machine learning and their combinations in [5].

Although, machine learning enables an image processing system to recognize the unseen objects, which are similar with the training objects. However, machine learning doesn't allow the system to update the generated classifier [6]. Therefore the system is not able to recognize new objects, which deviate from the already learned objects. For this reason, incremental learning is investigated. In [7] an incremental learning based on support vector machine, while in [8] an incremental learning based on neural network are introduced. Incremental learning has been applied in real application. In [10], an incremental learning method is used to classify scene, while in [11] for robust visual tracking.

Incremental learning is a promising solution which overcomes the shortcoming of machine learning. However, from engineering perspective, there are some problems in practice of incremental learning. How to treat the new emerging objects (add the new objects into an existing class or create a new class for the new emerging objects)? Which incremental learning methodology is to choose? How to realize the interaction between the user and image processing system, so that the image processing system is under control?

Taking the previous questions into account, a design method of an adaptive image processing system based on incremental learning for industrial applications is proposed in this paper. The outline of this paper is presented as follows: in section 2, human incremental learning is discussed with two examples. Inspired by human learning, a novel learning architecture based on incremental learning is developed in section3. Based on the learning architecture, an adaptive image processing system is presented in section 4 and the preliminary implementation is presented in section 5. Finally a brief conclusion is given in section 6.

II. HUMAN INCREMENTAL LEARNING

Before introducing the proposed system, the mechanism of human incremental learning is investigated. In [12] and [13], human learning process is supported to be an incremental learning process, which enables human to learn new objects, so that human can adapt himself to the new environment. Human learning can be distinguished into knowledge integration and reconstruction shown in Fig. 1. Assuming that a person possesses a previous knowledge that, blue triangles are objects of type A, and blue rectangles are objects of type B. Due to the changed environment, he receives a new knowledge that, a yellow triangle is also the object of type A. In this condition, he will consider that, these two knowledge are essentially not contradictory with each other. Because the objects of type A

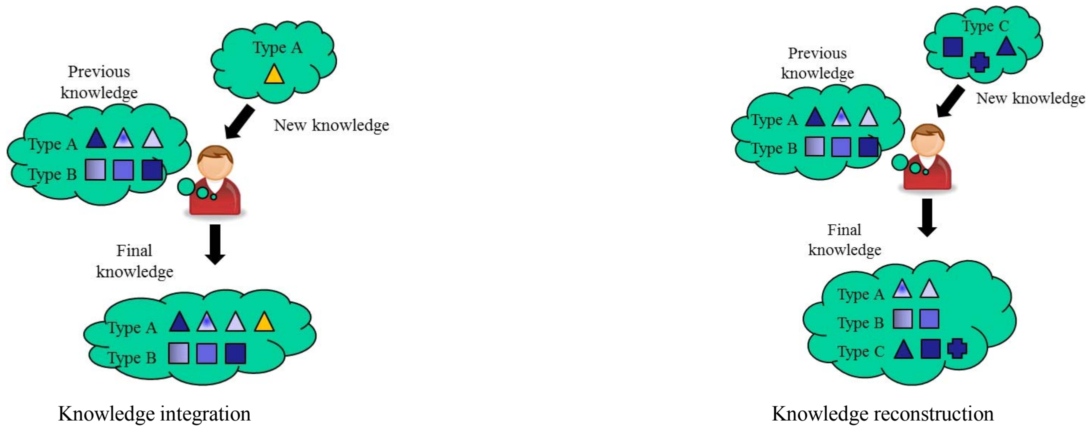

Fig. 1. Illustration of human incremental learning (left: knowledge integration, right: knowledge reconstruction).

have a common trait: they are triangles. Therefore he obtains a final knowledge that triangles are objects of type A, while rectangles are objects of type B. The learning process mentioned above is called knowledge integration.

If the new knowledge states that the dark blue triangles, crosses and rectangles are objects of type C, the human will get confused. Because his previous knowledge tells him that triangles stand for type A, and rectangles stand for type B. In this case, he tries to rebuild his knowledge space, so that the dark blue objects are considered to be new object type of C. The above mentioned knowledge rebuilding process is called knowledge reconstruction.

III. A Proposed Learning Architecture

The contribution of this paper is to propose a novel image processing system, which consists of three layers: execution, learning and user. Since the learning layer is the core layer, it is reasonable to discuss the learning layer before introducing the whole image processing system. Inspired by the human incremental learning process, a novel learning architecture is proposed, which consists of two modules: an adviser and incremental learning (see Fig. 2). The adviser is composed of data consistency test and a selector. The incremental learning consists of ensemble learning and data accumulation. The data of learned objects are stored in the previous database, while the data of new objects in the new database. The previous database was used for generating the previous classifier.

A. Adviser

Generally two kinds of algorithms are considered to be candidate for data consistency test (DCT). One is distance based (e.g. Euclidean, Mahalanobis), the other is statistic based (e.g. discriminant function analysis). Data consistency test is used to check the relationship between the previous and new database.

Fig. 3 illustrates data consistency test by measuring Euclidean distance in feature space. Assuming that the previous database consists of *2* classes: class *A* and class *B*. The new dataset can be a single sample or a new class including a set of samples, which is notated by $\boldsymbol{S}$. S_c is the centroid of $\boldsymbol{S}$. D_A and D_B indicate the distance between S_c and the two classes. θ is a distance threshold configurable by user. The data consistency test is carried out by two levels of test. At the first level, D_A and D_B are compared with θ. If D_A and D_B are smaller than θ, user is suggested to create a new class. In this case, data accumulation methodology as an incremental learning will be chosen. The introduction of θ is to discard the outliers (e.g. human may categorize a product of C into the products of B). At the second level, D_A is compared with D_B. The smaller distance suggests the new objects belong to that class. In this case, ensemble learning is chosen. Through data consistency test, the relationship between new objects and

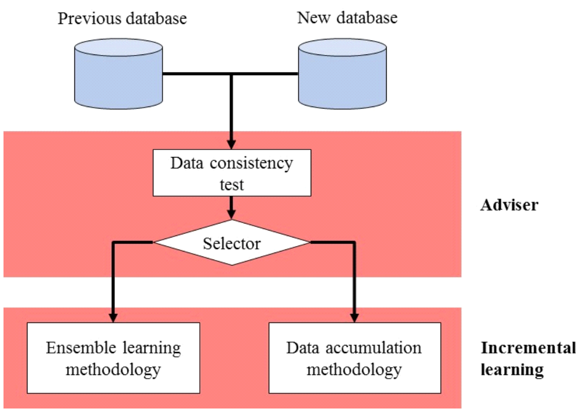

Fig. 2. A proposed learning architecture.

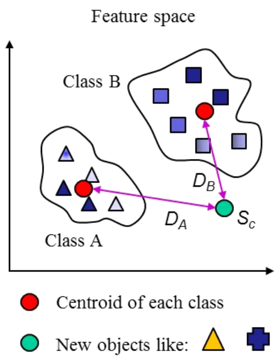

Fig. 3. Illustration of data consistency test

already learned objects can be estimated. Data consistency test is crucial to its following procedure - selecting a proper incremental learning to generate a new classifier.

B. Incremental Learning

In [14], two types of incremental learning methodologies are summarized and differentiated into data accumulation and ensemble learning methodologies. In data accumulation methodology, the old classifier needs to be discarded. A new object database is obtained by fusing the previous and new database. The new database is utilized to generate a new classifier. The incremental learning applied in [10] is a kind of data accumulation methodology. This approach accesses the previous database instead of utilizing the old classifier (class boundaries). Therefore, the knowledge base is reconstructed by data accumulation methodology. Differ from the data accumulation methodology, the ensemble learning methodology does not access the previous database. For each new database an incremental learning is activated for creating a new classifier. The new and existing classifiers will afterwards put into a voting algorithm for generating a composite classifier, which is composed of a set of classifiers. The *Learn++* in [8] and *Learn++.NC* in [9] are typical ensemble learning. Comparing to data accumulation methodology, the ensemble learning methodology integrates the new knowledge into previous knowledge.

IV. AN ADAPTIVE IMAGE PROCESSING SYSTEM

Based on the new learning architecture, an adaptive image processing system is developed in Fig. 4, which is composed of three layers: *execution*, *learning* and *user* layers. In the *execution* layer, a conventional image processing is constructed. Through the *learning* layer, the *classifier* in *execution* layer can be updated by applying incremental learning. The interaction between system and user take places via the *user* layer.

The conventional image processing system is constructed in the *execution* layer, which includes a *manipulator*, *image processing* and a *classifier*. Unsorted products are captured by a camera system (involved in *image processing*) and then analyzed by image processing algorithm. The analysis result

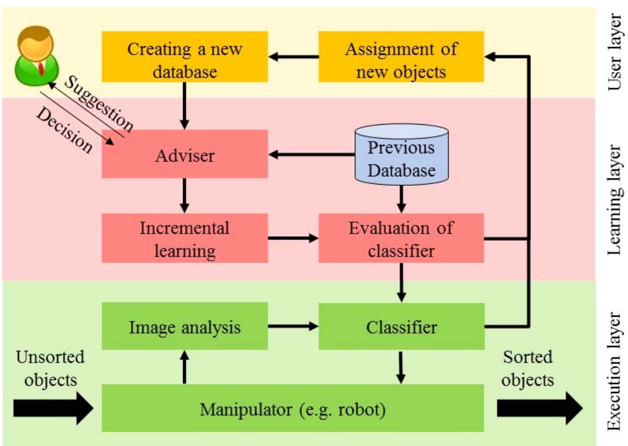

Fig. 4. A three-layer image processing system.

will be sent to a *classifier*, which has been developed in development phase and possesses a previous knowledge (class boundaries). It is known that the conventional image processing system is not able to learn new product types. Therefore, the new product types can only be wrongly classified or not able to be classified. The objects are so called unknown objects.

The unknown objects are recorded and collected by quality assurance, i.e. system user. System user has two treatments to the collected objects: either add them into the existing classes, or create new classes for them. This process is called *assignment of new objects*. Afterwards, a new database can then be created. Here, a new problem may emerge. *Assignment of new objects* is a highly subjective processing. User may assign an object into a wrong class (e.g. assign an apple as orange) without any consideration of the real data distribution in feature space. In order to reduce this kind of risk, an *adviser* is introduced in simulation layer. Details about *adviser* have been discussed in the previous sections. In addition, the *adviser* is able to interact with user by giving user a proper suggestion and receiving final decision from user. Then the *adviser* can choose a proper incremental learning methodology to generate a new *classifier*. Before the new *classifier* can replace the old one in execution layer, it has to be evaluated by providing previous database for classification. If the classification result is acceptable, the new classifier can replace the old one in *execution* layer. If not, the generated classifier should be discarded, and user needs to reassign the new objects. The processes above should be redone until an acceptable classifier is obtained.

The advantage of the three-layer image processing system is to integrate the learning process in the layer - *learning*, so that it is not necessary to shut down the whole system for updating the classifier. The adviser serves as an observer and counselor, which can estimate the relationship between new and previous data. It can also advice user to choose a proper solution. The adviser reduces the risk at having adding a wrong class or samples into existing classes. Through *user* layer, user is able to influence the learning process.

V. IMPLEMENTATION

In IAS (Institute of Industrial Automation and Software Engineering), the demonstrator of an adaptive image processing system is in building within the framework of an internal project “intelligent image processing”. The demonstrator is built with the help of IAS colleagues and students. The demonstrator includes an Ethernet-Color Camera JAI AB-201 GE (image size 1920*1080) with an objective 2/3” C 16 mm F1.4, two LED lamps.

The software of image processing part was developed in the platform of *LabVIEW*, while incremental learning was realized in *Python*. In the software, SVM is applied in data accumulation methodology for knowledge reconstruction. The ensemble learning techniques - *Learn++* and *Learn++.NC* are realized for knowledge integration (see Fig. 5). For the module *adviser*, two kinds of algorithms are considered: distance and statistic based. Distance based algorithms are Euclidean, Mahalanobis and Bhattacharyya. Statistical based algorithms

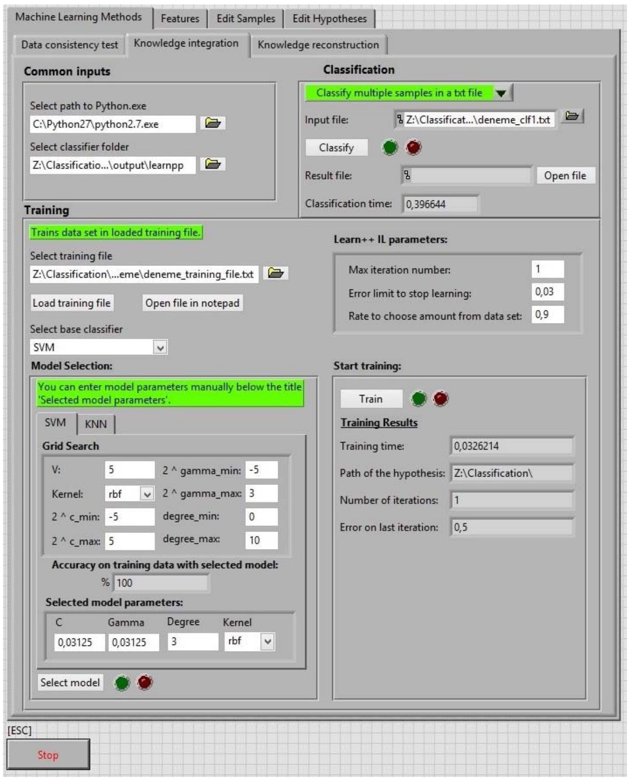

Fig. 5. A temporary program for the adaptive image processing.

are Mann-Whitney-Test and Discriminant Function Analysis (Linear Discriminant Analysis, and Multiple Discriminant Analysis). Momentary, a Mann-Whitney-based data consistency test has been realized to check the similarity level between new samples and the existing classes.

The user layer is still in development. To increase the usability, the global user interface (GUI) will also be improved in the future. The software has been tested in variant test cases by providing the images of agricultural products. The accuracy of recognizing new objects is between 60-90%, without the consideration of influence of features and data distribution. Therefore, in the near future, the feature selection algorithms will be integrated into the software in order to reach a stable recognition of new objects. In addition, the prevalent machine learning, like KNN and bayesian, will also be integrated into the existing software. A robot with a universal gripper will be equipped for testbed.

VI. CONCLUSION

Due to the unchangeable class boundaries of machine learning, the conventional image processing systems are not able to learn new objects and always meet their limitation in real application. Therefore, a three-layer image processing system is proposed. The overall system consists of execution, learning and user layers. In the learning layer, an adviser is applied to estimates the relationship between new and already learned objects and advices user to choose a proper solution. The application of an adviser reduces the risk at having adding a wrong class or samples into existing classes. In addition, user is able to influence the learning process through user layer by modifying parameters in the module of adviser.

Comparing to the conventional image processing system, the adaptive image processing system is able to learn new objects, and much robust to user desire. It is a potential image processing system for vision-based detection, where the target objects don't have a standard pattern. For instance, every agricultural product appears differently from each other. Furthermore, unlike industrial product, the quality of agricultural products is quite dependent on weather, stocking condition, customer flavor and so on. Therefore a constant quality standard is not feasible. In this case, a dynamic classification is required. In the future, IAS will try to utilize adaptive image processing in sorting building waste, which always have variant appearance and are difficult to recognize.

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