# A new scheme of merger information based on accuracy for image classification

Sébastien Desbouchages, Noël Richard, Anne-Sophie Capelle-Laizé
SIC Laboratory, Bâtiment SP2MI, Téléport 2, Boulevard Marie et Pierre Curie,
BP 30179, 86962 Futuroscope Chasseneuil, FRANCE
sebastien.contact@gmail.com

***Abstract*—In this paper, we introduce the use of accuracy criterion, estimated for each data sample in addition of the data feature. This complementary information is used during the combination of features to weight the data influence to produce a decision in a combination scheme. The major idea lies in the fact that all extracted measures or features are stained of errors, inaccuracy, and that kinds of errors must be taken into account during the combination and conflict management. We show in a generic case, how to express the accuracy criterion and how to use them in a belief function. In a classical classification problem, we proof also the contribution of the accuracy information in the improvement of the classification results.**

**Keywords: Accuracy, Belief Function, Conflict, Dynamic Feature Selection.**

## I. Introduction

Image processing methods belong to approach of non destructive testing. All of these applications come from the science of measurement for which accuracy, systematic bias are critical parts. From another point of view, image processing comes also from computer sciences and inherits from this domain lot of algorithms and developments. In such context, digital information is considered exact and complete. Since the last decade, image processing progress comes from computer sciences and the link between the metrological purpose and the image content are systematically forgotten.

In this work, we introduce accuracy criterion estimated for each feature computed from image data (section II). We define that each image property as histograms, texture characteristics, etc. should be involved in this accuracy criterion, which expresses how the computed data reflect the image content. If the processing chain use only one feature to analyze the data, the accuracy criteria has few incidence in the decision, in return if several features are computed this criteria should be used to dynamically choose or weight the decision in a combination scheme.

Such system is presented in this paper (figure 1) and included 4 steps: feature extraction (section II-A), accuracy measurement(section II), first labelisation ((section II-C) before the combination of the labels with taken into account of the feature accuracy (section II-D). To show the improvement due to this novel approach, we develop an example based on low-level optical character recognition for the MNIST database [1], [2] using three shape features (section IV).

## II. Accuracy measurement

By definition, the base of metrology is the definition, realization and dissemination of units of measurement [3], measured properties being quantized by assigning a property value in some multiple of a measurement unit. But from one of the first definition , notions of uncertainty and error are described as inseparable from the measure [4], [5]. Different standard informations associated to the measure are defined :

- *Accuracy* that is the degree of exactness which the final product corresponds to the measurement standard.
- *Precision* that refers to the ability of a measurement to be consistently reproduced
- *Reliability* that refers to the consistency of accurate results over consecutive measurements over time.
- *Traceability* that refers to the ongoing validations that the measurement of the final product conforms to the original standard of measurement.

In this work we use features for which the ability to describe the image content could be specify. In such cases, we can define the reference as the data set completely described without loss. Accuracy could be expressed as the normalized distance between the reference and the data described by the feature. Thus a constraint appears in our scheme : the selected feature must be invertible, ie, an image can be reconstructed from its values.

### *A. Shape descriptors and image reconstruction from them*

For the validation, we chosen to work with shape descriptors and particularly with Cartesians, centered and Zernicke moments, greatly used in image processing(section II-A). In such applications, moments are combined to produce more informative form, the invariants. Unfortunately, if it is possible to reconstruct image from moments, it is not possible from more complex information as the invariant. Upon the application problematics, it is not a good choice because the centered and Cartesian moments are strongly correlated. Nevertheless, we are interested to know how the combination could solve such difficulties.

Shortly, the shape descriptors are defined as follows

- ***Cartesian's moments :*** The descriptors are the simplest form obtained from the discrete moment computed from

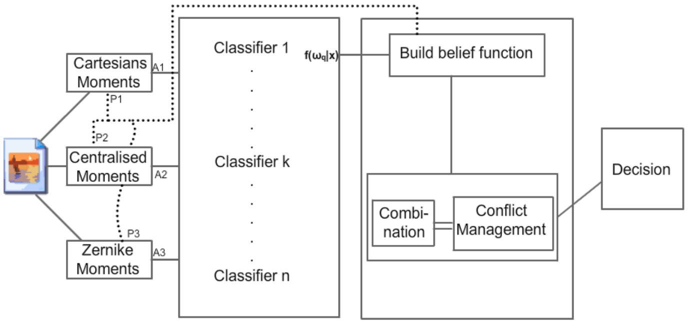


Figure 1. Combination system of local decision with accuracy integration

pixels values: $P_{xy}$. The moment $m_{pq}$ is defined by :

$$m_{pq} = \sum_{x=1}^{M}\sum_{y=1}^{N} x^p y^q P_{xy} \tag{1}$$

In particular, the image gravity center of coordinates $(\widehat{x}, \widehat{y})$ is obtained by zero-order and one-order moments :

$$m_{00} = \sum_{x=1}^{M}\sum_{y=1}^{N} P_{xy} \quad \text{and } \widehat{x} = \tfrac{m_{10}}{m_{00}}, \quad \widehat{y}\frac{m_{01}}{m_{00}}$$

- ***centered's moments :*** These descriptors are deduced from the Cartesian moments by centering the image content around gravity center of the image :

$$m_{pq} = \sum_{x=1}^{M}\sum_{y=1}^{N} (x-\widehat{x})^p (y-\widehat{y})^q P_{xy} \tag{2}$$

- ***Zernike's moments :*** The Zernike moment of $m+n$ order is defined by :

$$A_{mn} = \frac{m+1}{\pi}\sum_x\sum_y P_{xy}\overline{V_{mn}(x,y)} \tag{3}$$

where $V(m,N)$ is the Zernike polynomial expressed in polar coordinates:

$$V_{mn}(r,\theta) = R_{mn}(r)\exp(in\theta) \tag{4}$$

$$R_{mn}(r) = \sum_{s=0}^{\frac{m-|n|}{2}} (-1)^s F(m,n,s,r) \tag{5}$$

$$F(m,n,s,r) = \frac{(m-s)!}{s!(\frac{m-|n|}{2}-s)!(\frac{m-|n|}{2}-s)} r^{m-2s} \tag{6}$$

Due to the unicity theorem, the sequence of $m_{pq}$ moments is defined in a single manner from the $P_{xy}$ pixels sequence and conversely the $P_{xy}$ is defined in a single manner by the $m_{pq}$ moments. We can describe and reconstruct an image from the complete set of moments $m_{pq}$ or $A_{mn}$, that is defined for a sufficiently high order. When the order is not sufficient, the image reconstruction is approximative and more or less details are omitted. From the above shape descriptors, we can expressed the reconstructed image $\widetilde{P}_{xy}$ , computed from the moments. Shortly, the shape descriptors are defined as follows

- ***Cartesian's moments :*** Shutler [6] explain that we can retrieve a function $\widehat{f}(x,y)$ if we know all moments $M_{pq}$ of $f(x,y)$ function

$$\widehat{f}(x,y) = \sum_{p=0}^{N_{Max}}\sum_{q=0}^{N_{Max}} \widehat{f}_{pq} x^p y^q, N_{Max} = p+q \tag{7}$$

It's necessary to calculate constant coefficient $\widehat{f}_{pq}$ for obtain same moments for $\widehat{f}(x,y)$ and $f(x,y)$ functions

$$M_{pq} = \sum_i\sum_j \widehat{f}_{ij}\frac{1}{(i+p+1)(j+q+1)} * (1-(-1)^{i+p+1})(1-(-1)^{j+q+1}) \tag{8}$$

- ***centered's moments :*** Used the same processus of Cartesian's reconstruction with centered coordinates

$$\widehat{f}(x,y) = \sum_{p=0}^{N_{Max}}\sum_{q=0}^{N_{Max}} \widehat{f}_{pq}(x-\widehat{x})^p(y-\widehat{y})^q \tag{9}$$

- ***Zernike's moments :*** According to Shutler [6], Khotanzad [7] reconstruct function $\widehat{f}(x,y)$ with :

$$\widehat{f}(r,\theta) = \sum_{m=0}^{N_{Max}}\sum_{n>0}^{N_{Max}} A_{mn}V_{mn}(r,\theta) \tag{10}$$

$m-|n|$ even and $|n| \le m$. After development we obtain :

$$\widehat{f}(r,\theta) = \sum_{m=0}^{N_{Max}}\sum_{n>0}^{N_{Max}} (C_{mn}\cos(n\theta) + S_{mn}\sin(n\theta)R_{mn}(r) + \frac{C_{m0}}{2}R_{m0}(r)) \tag{11}$$

$C_{mn}$ is real part of $A_{mn}$ with :

$$C_{mn} = \frac{2m+2}{\pi}\sum_m\sum_n f(r,\theta)R_{mn}(r)\cos(n\theta) \tag{12}$$

and $S_{mn}$ is imaginary part with :

$$S_{mn} = \frac{-2m-2}{\pi}\sum_m\sum_n f(r,\theta)R_{mn}(r)\sin(n\theta) \tag{13}$$

For all the expression, the $\widetilde{P}_{xy}$ values are defined on integer domain and not in binary manner, so an additional operation is required to binarize the reconstructed image. To find the good threshold, the accuracy criterion is used in a closed loop function to find the value which gives the minimal distance between the reconstructed image and the original ones.

$$\tau_b = \arg_{0\le\tau\le\tau_{max}} d(P(x,y), \widetilde{P}(x,y)) \tag{14}$$

### *B. Distance formulation*

To be coherent with the accuracy definition, we need a function defined between 0 and 1, which expressed how the reconstructed image $\widetilde{P}$ reflected the original image $P$. Such expressions are well known and based on a description of four sets, $L_{00}$ the true negative and $L_{11}$ the true positive values (ie the pixels well reconstructed) completed by the $L_{10}$ and $L_{01}$

values for the errors of reconstruction. Thanks to these sets, we can define the accuracy criterion :

$$\rho(P, \widetilde{P}) = \frac{l_{00} + l_{11}}{l_{00} + l_{11} + l_{10} + l_{01}} \quad (15)$$

For a perfect reconstruction, without error, the accuracy reach 100% and linearly decreases on each sides of this optimum. An reconstruction error on white or black pixel induce the same loss of accuracy.

### C. Accuracy and classification

Before presenting how to combine the accuracy criterion in the belief theory, we will see how this criterion varies on our test data. Figure 2 shows for each class of the datasets, the cumulative histograms of accuracy according to the classes reconstructed with Zernike moments at 15th order. This curve allows to know the rate of samples for each classes where accuracy is lower than a specific rate. In particular, we show that more than 20% of samples have an accuracy lower than 50% and that rate grow up to 45% in the case of the class *4*!

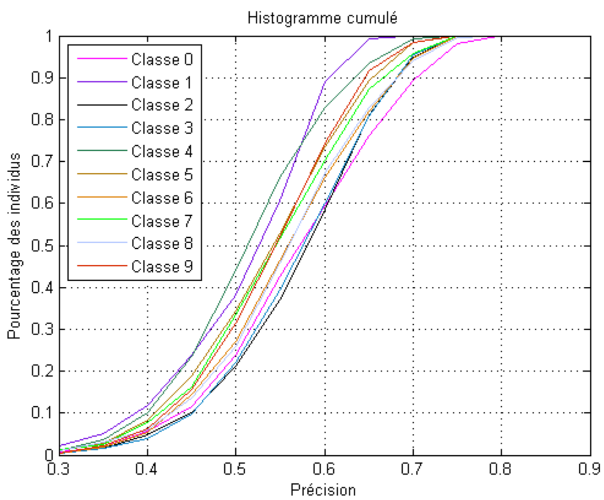


Figure 2. Cumulated histogram of the accuracy according to the classes reconstructed with Zernike moments at 15'th order

### D. Integration in TBM

Our purpose is to combine informations from the computed moments to produce a decision of classification. As we can't use directly the vector of moments in the beliefs functions, we needs to transform these vectors in discrete labels by classifiers.

To construct belief functions, several estimate models are described in the literature [8] [9] [10]. In this paper, we use model 2 of Appriou [11]. The beliefs functions are produced starting from the posterior probabilities resulting from the classifiers $f(x|\omega_q)$ Posterior probabilities

$$\begin{aligned} m(\omega_q) &= 0 \\ m(\overline{\omega_q}) &= \alpha_q(1 - R.L(\omega_q|x)) \\ m(\Omega) &= 1 - \alpha_q(1 - R.L(\omega_q|x)) \end{aligned} \quad (16)$$

where $R$ is a normalization factor of $L$ included in $]0, \max_{q\in[1,N]}(L(\omega_q|x))^{-1}]$ and $\alpha_q$ is the weakening factor which corresponds in the Appriou's theory to the reliability of a source to decide $\omega_q$ [12]. To embedded our accuracy criterion in the Appriou's model, we modify the definition of $\alpha$ and replace it by our accuracy criterion. In further works, we will combine these two complementary informations. For this works, $\alpha_q$ becomes $\alpha = \rho(P, \widetilde{P}))$ and depend only on the features computed from the samples. Our intention is not to replace the reliability (given by confusion matrix) but rather to show the contribution that can give accurate.

## III. Information fusion

To obtain belief functions, we need a classifier step but each classifier could be analyzed as a system which organize the features space in regions. As this spatial organization is great dependent of the classifier, it is not possible to choose the right one for all the samples and all the classes. We decided to combine the decision produced by several classifiers for our three moments.

### A. Conjunctive combination

Evidence theory offers appropriate aggregation tools to combine informations [13]. For each classifiers $\mathcal{S}$ and each classes $\mathcal{C}$, we obtain this matrix of beliefs functions. The rule of combination proposed by Smets is thus defined by :

$$\begin{aligned} m_\cap(A) &= \sum_{B\cap C=A}^{M} m_1(B).m_2(C) \\ m_\cap(\emptyset) &= \sum_{B\cap C=\emptyset}^{M} m_1(B).m_2(C) \end{aligned} \quad (17)$$

However, this combination generates belief on $m(\emptyset)$, the assumption of the closed world is not respected.

### B. Conflict management

Upon Colot and Lefevre, there are three reasons why a conflict appears when combining evidence [14].

- An aberrant measurement given by a sensor
- Imprecise model of the belief function may provide a conflict
- Sources to be aggregated are numerous, a conflicting mass can be induced even if there sources agree

Our point of view extend clearly this purpose, by integrating the unability of a pair *(feature, classifier)* to well describe a particular sample due to the bias, uncertainty, inaccuracy attached to the measurement.

Technically, the conflict is associated with the mass $m(\emptyset)$ during the combination step. In this study we have tried three methods of conflict management. First one is normalization by conflict proposed by Dempster-Shafer :

$$\begin{aligned} m_{DS}(A) &= \frac{m_\cap(A)}{1 - m_\cap(\emptyset)}, A \neq \emptyset \\ m_{DS}(\emptyset) &= 0 \end{aligned} \quad (18)$$

The second one is the association of the conflict on $m(\Omega)$. Yager [15] postulates that the frame of discernement is exhaustive (closed-world assumption). Thus, the conflit is distribute on several hypothesis $\omega_q$ during pignistique step.

$$\begin{aligned} m_Y(A) &= m_\cap(A) \\ m_Y(\emptyset) &= m_\cap(A) + m_\cap(\emptyset) \end{aligned} \tag{19}$$

The third one is the distribution of the conflict on the union of the assumption generating it proposed by Dubois-Prade [16]. This rule of combination is better adapted and more specific than Yager's rule because conflit is only distributed on hypothesis who generate it.

$$m_{DP}(A) = m_\cap(A) + \sum_{B\cap C=\emptyset B\cup C=A}^{M} m_1(B).m_2(C) \forall A \subseteq \Omega$$

Yager and Dubois-Prade combination rule are commutative but not associative [17], [18], it's therefore necessary to choose combination order. Figure 3 show the combination order used in a three step of combination :

- Classifiers combination : All belief functions associated with the same classes and from different classifiers are combined, each matrix represented for this step in figure 3 is the same form as that presented figure **??**.
- Attributes combination : All belief functions associated with the same classes and from different attributes are combined
- Classes combination : All functions from different classes are combined, this step is the most expensive in terms of computing time. Finally we obtained a unique belief function.

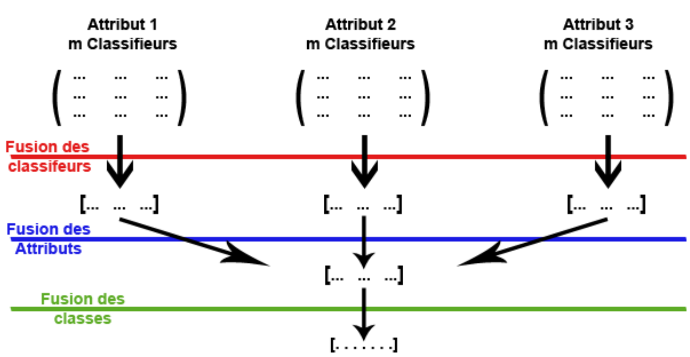


Figure 3. Combination protocol

## IV. Results

The following applications are based on the decisions resulting from 6 classifiers Quadratic Bayes Normal Classifier (QBNC), Fisher's Least Square Linear Classifier (FLSLC), Nearest Mean Classifier (NMC), $k$ Nearest Neighbors Classifier (KNNC), Parzen Classifier (ParzenC), Naive Bayesian Classifier (BayesN). They were chosen because they have very different behavior. Each of those classifiers has been first trained and tested on all the data sets to compute global performances. Training and testing data sets have been build using *bootstraping* [19] with original data, with null intersection between the sets each time. KNNC, ParzenC and NMC are *adaptative*, their parameter value (i.e. $k$ for KNNC and ParzenC) is optimized during the training phase. Besides, once the parameter fixed, it is not recomputed during the recognition.

### A. Classification without accuracy and information combination

In first step, we will compute the ability of each classifier to produce the right decision from each of the three moment described at 15 order. Table I presents the error rate obtain by each classifier. Without surprise, the $k$ Nearest Neighbors Classifier is the more reliable for the three moments, but the Fisher's Least Square Linear Classifier reach better results for Cartesian and centered moment. Due to the complexity of the samples cloud in each features space, Bayes approaches are in difficulty.

| | Moments | | |
|---|---|---|---|
| | Cartesians | Zernike | Centered |
| KNNC | 0,33 | 0,08 | 0,38 |
| QBNC | 0,79 | 0,90 | 0,73 |
| FLSLC | 0,15 | 0,14 | 0,13 |
| NMC | 0,65 | 0,24 | 0,55 |
| ParzenC | 0,90 | 0,90 | 0,90 |
| BayesN | 0,53 | 0,78 | 0,56 |

Table I
Error rate for each classifiers

### B. Application 2 : the complete scheme

In this application, we use the probabilities of density provided by the classifiers and add the accuracy measurement to combine the results. The curves in figure 4 show the error rate in function of the rejection rate, defined by a threshold applied on the pignistic probability.

For null rejection rate, we note that the conflict management does not improve the results. Then when the rejection rate increase, the impact of the conflict management increases too to reduce the error rate. The result without rejection is near from 10%, very closed of the best result obtain by the $k$ Nearest Neighbors Classifier alone. It is very interesting because we could have awaited results quite worse, following the previous application. In fact, the diversity of classifier allow to find a coherence between classification results.

When the rejection rate increase, the decision is more difficult to take and the conflict management allow a better construction. Nevertheless, the profit does not exceed 2%, which is lower than the expected increase. In addition, results obtained by Dubois-Prade and Yager formulations are identical.

The confusion matrix reveals (Figure 5) that certain classes generate more problems for the recognition. For example, we

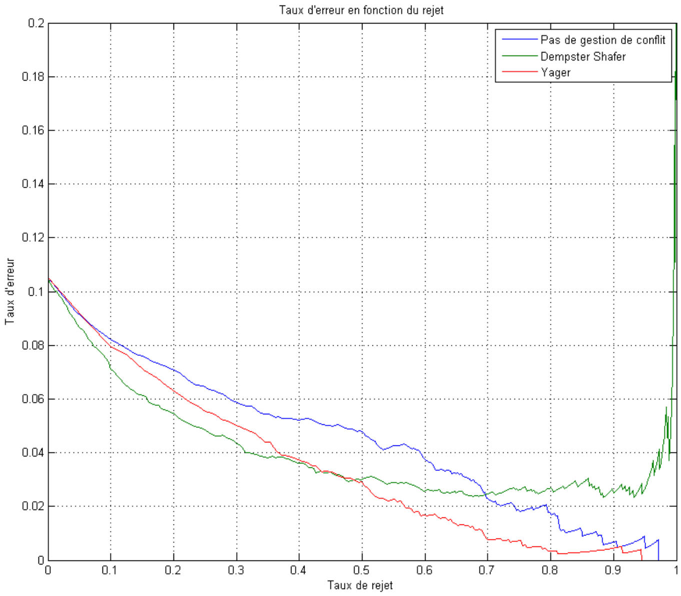


Figure 4. Error rate vs. rejection rate for decision on 10 classes

observe that number 5 is regularly confused with number 1 or 3. Such result show the interest to split the problem in a decision tree.

To end with these results, we can see that for the conflict management with Dempster-shafer formulation, there is a serious degradatation of the results for high rejection rate. This fact is due to some samples that are clearly closed to a wrong classe and mistake the system with a simple conflict management.

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0,97 | 0,01 | 0 | 0 | 0 | 0 | 0,01 | 0 | 0 | 0 |
| 1 | 0 | 0,99 | 0 | 0 | 0 | 0 | 0,01 | 0 | 0 | 0 |
| 2 | 0,02 | 0,03 | 0,84 | 0,03 | 0,01 | 0,01 | 0,03 | 0,02 | 0,02 | 0 |
| 3 | 0,01 | 0,02 | 0 | 0,9 | 0 | 0,02 | 0 | 0,02 | 0,01 | 0,02 |
| 4 | 0 | 0,03 | 0 | 0 | 0,87 | 0,01 | 0,02 | 0 | 0 | 0,06 |
| 5 | 0,01 | 0,05 | 0 | 0,08 | 0,01 | 0,78 | 0,01 | 0,01 | 0,02 | 0,01 |
| 6 | 0,01 | 0,01 | 0,01 | 0 | 0 | 0,02 | 0,95 | 0 | 0 | 0 |
| 7 | 0 | 0,02 | 0 | 0 | 0 | 0,01 | 0 | 0,92 | 0 | 0,04 |
| 8 | 0,02 | 0,04 | 0,01 | 0,04 | 0,01 | 0,04 | 0 | 0,01 | 0,81 | 0,02 |
| 9 | 0,01 | 0,01 | 0 | 0,02 | 0,04 | 0 | 0 | 0,02 | 0,01 | 0,89 |

Figure 5. Confusion matrix

## V. Discussions

As we can see in result section, the conflict management proposed by Yager and Dubois-Prade provide same results. As the two expressions are different, the problem can come only from the distribution of the masses of belief. In particular, this problem is due to the fact that Appriou model 2 don't generate conflit between two noncomplementary hypothesis. As shown in figure 6, the intersect hypothesis who appears during combination of elementary masses sets $\{m(\omega_q), m(\overline{\omega_q}), m(\Omega)\}$ limits the conflict production to the mass $m(\emptyset)$. We show the combination in the case of a combination of 4 elementary mass functions build with Appriou 2 model. Each bar represents the 16 parties as possible for 4 classes. A filled square represents a focal element of the belief function ($M^{12}$ contains $\{m(\overline{\omega}_1), m(\overline{\omega}_2), m(\overline{\omega_{12}}), m(\Omega)\}$ focal elements). The red lines are the combinations that generate conflict. We can see only one conflict occurs during the process of combination. This conflict is due to combination of $m(\omega_4)$ and $m(\overline{\omega_4})$. Thus, during the conflict management, Yager and Dubois-Prade methods will allocate both the conflict with the mass $m(\Omega)$.

This observation raises two issues:

- Several methods of conflict management lose interest
- Conflict is almost nonexistent

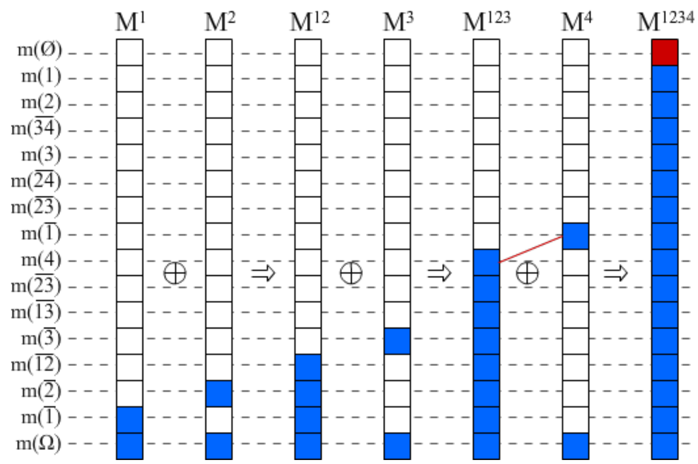


Figure 6. Conflict generate with belief create by Appriou 2 model

Figure 7 illustrates the same case of combination excepting that elementary belief function was created with Appriou 1 model. With this approach, the conflict appears at every stage of combination. Moreover, it will not come exclusively from a combination of complementary mass. In this case, Yager and Dubois-Prade methods will not provide the same results.

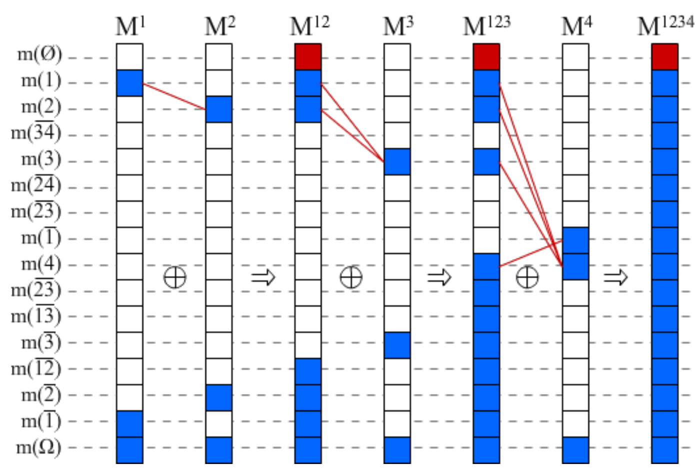


Figure 7. Conflict generate with belief create by Appriou 1 model

## VI. Conclusion

In this work, we proposed to integrate accuracy criteria with the feature information in a combination scheme of several features. We have shown the relevance of the accuracy criteria in a classical application and how the ability of a feature to describe the sample has great variations. A feature could be well adapted for one sample and totally maladjusted to one other. To show the impact of such point of view, we have extended the Appriou's formulation for the Transfer Belief Model to integrate the accuracy criteria. Then we have shown how the final error rate could be improved.

We chosen to use two correlated features in our features set. In classical formulation of combination, the error's rate explode when these two features induce together bad decisions. Clearly, in such cases our hyphenation was that mistakes are due to features inaccuracy. In a classical formulation, when these two features are mistaken in front of the third, the decision tends to be wrong, when in our case if the feature accuracy is lower than 50%, the feature impact is reduced in the combination and the third feature take by opposition more weight.

By integrating feature accuracy in the belief function, we solve the problem induced by combining correlated features. It's a very interesting potentiality, because it allows combining several features with low constraints. This possibility simplifies the construction of image processing chain. Another interesting point of view is that the system dynamically combines the features to process the final decision. Because the accuracy is different between two samples, each static combination could only choose the less bad solution of combination defined by off-line learning. If the learning stage is well control yet with last scientific result, it greatly dependant from the learning set. Trough quality criteria and diversity measure, this quality could be managed by several approaches, but any is able to locally optimize the decision in on-line process. Our natural extension of the purpose it to work on dynamical image processing chain, with feed-back point managed par accuracy criterion.

Clearly, the proposed results are lower than the bests results obtained for the MNIST database, used in our experimental part. For example P.Shang [20] obtain a rate of recognition of 99,96% with 0,77% of rejection. But in such cases, features spaces are of higher dimension and with features of higher complexity. In [21] the same observation could be made. Our purpose was to show the relevance of the accuracy criteria for low level features, and naturally in future works by integrating others features higher results will be obtained.

In this work we don't use the notion of source quality defined by Apriou in his belief function. But now as we have shown the improvement obtained by the accuracy criterion use, we are able to combine these two kinds of information: the ability of the feature to be relevant for the decision $\omega_q$ and the accuracy of the feature to describe the sample $x$. Nerveless a simple multiplication could not solve the problem, and a more complex expression is needed.

Finally, the major problem to solve in this work lies in the choice of the conflict management formulation. As we have shown, in the example of the MNIST Database, the conflict management functions are not well adapted and in consequences have few improvement in the final result. Our initial choices was made upon the most classical way of the literature, now we need to explore more complex form to find the best appropriate formulation in our context of decision by taking into account of the feature accuracy.

## References


[1] Y. LeCun and C. Cortes, "The mnist database of handwritten digits," http://yann.lecun.com/exdb/mnist/, 1998.

[2] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," in *IEEE*, vol. 86, no. 11, November 1998, pp. 2278–2324.

[3] C. Dotson, *Fundamentals of Dimensional Metrology*, 5th ed. Delmar Learning, Novembre 2006.

[4] J. R. Taylor, *An Introduction to Error Analysis: The Study of Uncertainties in Physical Measurements*, 2nd ed. University Science Books,U.S, Juillet 1997.

[5] B. I. des Poids et Mesure, "What is metrology," http://www.bipm.org/en/convention/wmd/2004/, 2004.

[6] J. Shutler, "Statistical moments," *Computer vision online course*, 8 2002.

[7] A. Khotanzad and Y. Hong, "Invariant image recognition by zernike moments," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 12(5), pp. 489–497, 1990.

[8] T. Denoeux, "A k-nearest neighbor classification rule based on dempster-shafer theory," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 25, pp. 804–813, 1995.

[9] M. Rombaut and V. Berge-Cherfaoui, "Decision making in data fusion using dempster-shafer's theory," *In 3th IFAC Symposium on Intelligent Components and Instrumentation for Control Applications*, 6 1997.

[10] D. Gruyer, "Etude du traitement de données imparfaites pour le suivi multi-objet. application aux situations routières," Master's thesis, Université de Technologie de compiègne, 1999.

[11] S. Fabre, A. Appriou, and X. Briottet, "Presentation and description of two classification methods using data fusion based on sensor management," *Information Fusion*, vol. 2, pp. 49–71, 2001.

[12] A. Martin and C. Osswald, "Une nouvelle règle de combinaison répartissant le conflit - apllications en imagerie sonar et classification de cibles radar," *Revue Traitement du Signal*, vol. 24, pp. 71–82, 2007.

[13] T. Denoeux, "Conjunctive and disjunctive combination of belief functions induced by nondiistinct bodies of evidence," *Artificial Intelligence*, vol. 172, pp. 234–264, 2008.

[14] E. Lefevre, O. Colot, and P. Vannoorenberghe, "Belief function combination and conflict management," *Information Fusion*, vol. 3, pp. 149–162, 2002.

[15] R. Yager, "On the dempster-shafer framework and new combination rules," *Information Sciences*, vol. 41, pp. 93–138, 1987.

[16] D. Dubois and H. Prade, "Representation and combination of uncertainty with belief functions and possibility measures," *Computational Intelligent*, vol. 4, pp. 244–264, 1998.

[17] E. Lefevre, "Fusion adaptée d'informations conflictuelles dans le cadre de la théorie de l'évidence," Master's thesis, Institut National des Sciences Appliquées de Rouen, 2001.

[18] F. Janez, "Fusion de sources d'information défiinies sur des référentiels non exhaustifs différents," Master's thesis, Ecole doctorale sciences pour l'ingénieur de Nantes, 1996.

[19] L. Kuncheva, M. Skurichina, and R. Duin, "An experimental study on diversity for bagging and boosting with linear classifiers," *Information fusion*, pp. 245–258, 2002.

[20] P. Zhang, T. D.Bui, and C. Y. Suen, "A novel cascade ensemble classifier system with a high recognition performance on handwritten digits," *Pattern Recognition*, vol. 40, pp. 3415–3429, 2007.

[21] L. Xu, A. Krzyzak, and C. Y. Suen, "Methods of combining multiple classifiers and their application to handwritting recognition," *IEEE Transaction on Systems, Man, and Cybernetics*, vol. 22:3, pp. 418–435, 1992.