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Accurate target identification using multi-look fusion of low quality target signatures

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Abstract

Single-look identification procedure using one input at a time has been the principal mode of analysis used in the target recognition community for much of the past two decades. But it has been realized that the single-look approach can only achieve modest correct identification performance and this is not adequate for many target identification applications. Furthermore, in order for the single-look procedure to perform well, good target data quality is required. In this report, a multi-look method known as score-level fusion is investigated. It permits a significant improvement in the identification performance. Moreover, it does not require good quality target signature data; multiple signature samples of marginal quality may be used instead. Results from analysis using measured radar target data have shown quantitatively that the correct identification rate can be improved very dramatically. Furthermore, the score-level fusion method is very efficient; the identification performance increases exponentially with an increase in the number of samples used in the multi-look sequence. A qualitative characterization of the score-level fusion method based on the principle of averaging is given. It provides an intuitive understanding of this fusion process and how improvement in identification accuracy is achieved. The identification results obtained in this study suggest that quantity can be used to replace quality of the data to improve target identification accuracy. This has an interesting practical implication. With the advent of sensor technologies, large quantities of data of marginal quality can be captured routinely. This “quantity over quality” approach could maximize the exploitation of available data to provide reliable and robust identification. Thus, the score-level fusion method could have the potential of being developed into a disruptive technology for target identification and pattern recognition problems.

Résumé

Pendant la plus grande partie des deux dernières décennies, la communauté de la reconnaissance des objectifs a principalement employé comme méthode d’analyse la procédure d’identification monovisée, laquelle exploite les données obtenues qu’avec un un seul capteur. Toutefois, force est de constater que le rendement de l’identification correcte d’objectifs par l’approche monovisée est modeste et, qu’en outre, celle-ci n’est pas adaptée à plusieurs applications de l’identification d’objectifs. Qui plus est, la procédure monovisée ne donne de résultats corrects que si on l’applique qu’à des données de bonne qualité pour les objectifs. Dans le présent rapport, nous présentons notre étude d’une méthode multivisée nettement supérieure sur le plan de l’identification : la fusion au niveau des scores. En outre, pour bien fonctionner, cette méthode n’exige pas que les données de signature d’objectifs soient de bonne qualité, elle traite plutôt un grand nombre d’échantillons de qualité médiocre. Les résultats d’une analyse réalisée avec les données d’un objectif, obtenues par radar ont quantitativement montré que la méthode de fusion au niveau des scores pouvait grandement améliorer le taux d’identifications correctes. Qui plus est, elle est très efficace et son rendement augmente exponentiellement avec le nombre d’échantillons multivisées utilisés. Nous caractérisons qualitativement cette méthode qui repose sur le principe de la moyenne. Cette caractérisation apporte une compréhension intuitive du procédé de fusion et de la façon dont il améliore la précision de l’identification. Les résultats d’identification obtenus dans la présente étude suggèrent que l’on puisse augmenter la précision

d'identification des objectifs en accroissant la quantité de données plutôt qu'en en améliorant la qualité. Notre travail a des conséquences pratiques intéressantes. Avec l'apparition de nouvelles technologies de capteurs, on pourrait obtenir couramment de grandes quantités de données de qualité médiocre. Cette approche de « la quantité plutôt que la qualité » permettrait de maximiser l'exploitation des données disponibles et nous fournir des identifications fiables et solides. Ainsi, la méthode de fusion au niveau des scores pourrait constituer une *technologie de rupture* pour les problèmes d'identification des objectifs et de reconnaissance des formes.

Executive summary

Accurate target identification using multi-look fusion of low quality target signatures:

S. Wong; DRDC Ottawa TM 2008-251; Defence R&D Canada – Ottawa; December 2008.

Introduction or background: Identification algorithms are of practical interest for various military and security applications. These include Combat Identification, Aided Target Recognition, Low Probability of Intercept radar identification and human facial recognition. Much of the effort in the target recognition community so far has been devoted to achieving high identification accuracy using a single target signature as input to the identification process. It is found that the identification accuracy that can be achieved is modest and is dependent on the quality of the target signatures used. With sufficiently good signature quality, correct identification rate in the high eighties and low nineties percentage can be achieved readily. But in some applications, for example Combat Identification, identification accuracy better than 99% is sought. To improve on the accuracy, multi-look methods have been investigated, in which a number of signatures are used collectively to determine the identification outcome. Although the multi-look approach can improve the correct identification rate considerably, many commonly used multi-look procedures require good quality signatures since they are based on examining the collective identification evidence from a group of single-look samples. Hence, data quality still remains an important issue.

In this report, a different multi-look identification approach is examined. This method is known as the score-level fusion method; it fuses information from multiple input samples in making an identification decision. Results from this study have shown that the score-level fusion approach does not require good quality target signature data to achieve highly accurate identification; multiple samples of marginal quality may be used instead. No study has yet been reported in the open literature in examining the capability of an identification procedure that can make use of low quality target signatures, but produce highly accurate identification.

The superior performance of the score-level fusion method is illustrated in a comparative analysis against the well-known majority-vote method. The quality of the target signature data and the multi-look sample size are two major parameters that are used in evaluating the performance between these two multi-look methods.

Results: The majority-vote method is a well-established and commonly used algorithm for multi-look identification to improve identification accuracy. It produces an identification decision based on a particular target type appearing the most frequently from a series of single-look identification outcomes. However, its performance is highly dependent on the quality of the signatures. Using relatively good quality data such that the single-look correct identification rate is significantly above 50%, the majority-vote method can provide notable improvement to the identification performance. But for data of marginal quality, the majority-vote method does not provide any improvement at all. For example, when the signature quality is at such poor level that the single-look correct identification rate is less than 50%, the identification performance is actually worse by applying the majority-vote method. In contrast, the score-level fusion method is

found to be capable of providing a significant improvement to the identification performance irrespective of the quality of the target signature data. It achieves this by taking a different approach to multi-look identification. Instead of computing an identification decision from each input signature, the score-level fusion computes a series of “matching scores” from multiple input signatures. These matching scores are then combined to generate a single fused score for each of the target classes that are stored in the classifier. An identification decision is then made based on the fused scores. Using data of relatively poor quality, the score-level fusion has shown that it is capable of improving the correct identification rate from 37% (in single-look) to over 97% using a 20-look sequence. Moreover, the correct identification rate increases exponentially with an increase in the number of multi-look samples used. This represents a very effective means for improving the identification performance. In brief, what is original and innovative in this study is the demonstration of a process that enables significant improvement in target identification accuracy using multiple samples of marginal quality signatures.

Significance: Results from the score-level fusion method indicate that quantity can be used to replace quality of the data to improve the identification accuracy. This could have a profound implication for practical applications. With the advent of sensor technologies and deployment of multiple sensor platforms for surveillance, large quantities of data of marginal quality can be captured readily for intelligence exploitation; whereas, collecting quality data still presents a technical challenge and could also be more costly. The ability to maximize the exploitation of a large number of available data to improve on the identification performance could have significant impact in intelligence analysis. This “quantity over quality” approach could have the potential of being a disruptive technology for Defence and Security S&T applications, in particular, in the area of ISR. It can also be applied to other pattern recognition problems in general, for example, human biometrics such as face recognition. Thus, a special property of the score-level fusion method has been uncovered; that is, poor quality signature data can be of practical value and can be exploited. This study represents a major step forward in target identification algorithm development.

Future plans: So far, the score-level fusion method has been applied only to target signature identification analysis in the radar domain in our research activities. In this report, signatures of ground targets in the X-band (10 GHz) are analyzed and exceptionally good results have been achieved. In earlier work, in-flight aircraft signatures in the Ku-band (16 GHz) were examined. Excellent identification results have also been obtained. Investigation will be applied to the human facial recognition problem. A research project “Video-based facial recognition algorithm and system demonstration” is currently in progress to assess the score-level fusion method for video image data.

Furthermore, there is very little theoretical work on the score-level fusion method being reported in the literature. This presents a challenge and an opportunity to give the score-level fusion method a more precise mathematical description, providing a rigorous theoretical foundation. Further basic research would be desirable and of strategic value. A better conceptual understanding of the fundamentals could have significant impact in opening up new applications to other pattern recognition problems, particularly in the Defence and Security S&T area.

Sommaire

Accurate target identification using multi-look fusion of low quality target signatures:

S. Wong; DRDC Ottawa TM 2008-251; R & D pour la défense Canada – Ottawa; Décembre 2008.

Introduction ou contexte: Les algorithmes d'identification sont d'un intérêt pratique aux plans militaire et sécuritaire, pensons notamment à l'identification pendant le combat, à la reconnaissance assistée d'objectifs, à l'identification par radar à faible probabilité d'interception et à la reconnaissance des visages. Jusqu'à maintenant, la communauté de reconnaissance des objectifs a consacré une grande partie de ses travaux à accroître la précision de l'identification, à partir d'une seule signature d'objectif. Or, l'on a découvert que la précision d'identification que l'on pouvait obtenir était modeste et variait en fonction de la qualité des signatures d'objectifs employées. Ainsi, si l'on dispose de signatures dont la qualité est suffisamment bonne, on peut obtenir d'emblée un taux d'identifications correctes autour de 90 %. Toutefois, dans certaines applications, l'identification au combat notamment, cette précision doit dépasser 99 %. Pour la rehausser, on a réalisé des recherches sur des méthodes multivisées qui établissent une identification par l'emploi collectif de plusieurs signatures. Les méthodes multivisées pourraient grandement améliorer le taux d'identifications correctes. Toutefois, plusieurs d'entre elles sont fondées sur l'examen collectif de preuves d'identification à partir d'un ensemble d'échantillons monovisées et donc nécessitent des signatures de bonne qualité. Le problème de la qualité des données reste donc un enjeu important.

Dans le présent rapport, nous présentons notre examen d'une méthode différente d'identification multivisée : la fusion au niveau des scores qui arrive à une décision d'identification par l'intégration des informations de plusieurs échantillons à l'entrée. Nous avons montré que, pour arriver à une identification très précise, la fusion au niveau des scores n'exigeait pas de données de signature de bonne qualité, mais se contentait de plusieurs échantillons de qualité médiocre. Dans la littérature publiée, nous n'avons pas trouvé d'étude de la capacité d'une procédure d'identification pouvant produire des identifications de haute qualité, à partir de signatures d'objectifs de basse qualité.

Nous montrons le rendement supérieur de la méthode de fusion des scores, grâce à une analyse comparative avec la méthode bien connue du « vote majoritaire ». La qualité des données de signature et la taille des échantillons multivisées sont deux paramètres importants utilisés pour comparer les rendements de ces deux méthodes multivisées.

Résultats: La méthode du vote majoritaire est un algorithme bien établi et couramment employé pour améliorer la précision de l'identification à partir d'informations multivisées. Elle donne une décision sur l'identification en « élisant » le type particulier d'objectif le plus fréquemment retrouvé dans une série de résultats d'identifications monovisées. Ainsi, son rendement dépend fortement de la qualité des signatures. Si l'on dispose de données relativement bonnes dont la proportion de l'identification monovisée correcte est bien au-delà de 50 %, cette méthode améliorera considérablement le rendement d'identification. Si, par contre, les données sont

médiocres, elle n'apportera aucune amélioration. Par exemple, si la qualité des signatures est mauvaise au point que le taux d'identifications monovisées correctes est inférieur à 50 %, la méthode du vote majoritaire donnera un rendement pire. En revanche, nous avons trouvé que la méthode de fusion au niveau des scores améliorait grandement le rendement d'identification, quelle que soit la qualité des données de signature des objectifs. Cette indépendance par rapport à la qualité provient du traitement différent de l'identification multivisée : plutôt que de calculer la décision d'identification à partir de chaque signature à l'entrée, elle calcule une série de « scores appariés » à partir de multiples signatures à l'entrée. Ces scores appariés sont ensuite combinés pour produire un unique score fusionné pour chaque classe d'objectifs conservée dans le classificateur. La décision est ensuite prise à partir des scores fusionnés. Appliquée sur des données plutôt médiocres, la méthode de fusion au niveau des scores a pu améliorer le taux d'identifications correctes de 37 % à plus de 97 % en passant de données monovisées à séquence de vingt « visées ». Qui plus est, le taux d'identifications correctes augmente exponentiellement avec l'accroissement du nombre d'échantillons multivisées utilisés. Il s'agit d'un moyen très efficace d'améliorer le rendement d'identification.

Importance: Les résultats de la méthode de fusion au niveau des scores indiquent que l'on peut améliorer la qualité de l'identification en se fondant sur la quantité des données plutôt que sur leur qualité, ce qui pourrait avoir des conséquences importantes pour les applications pratiques. D'une part, l'apparition de technologies de capteurs et la mise en service de plateformes multicapteurs pour la surveillance nous permettent d'obtenir facilement de grandes quantités de données de qualité médiocre pour le renseignement; alors que la collecte de données de qualité constitue encore un défi technique possiblement plus coûteux. La capacité de maximiser l'exploitation d'un grand nombre de données disponibles afin d'améliorer le rendement de l'identification pourrait avoir un effet important pour l'analyse du renseignement. Cette approche de « la quantité plutôt que la qualité » pourrait constituer une *technologie de rupture* pour les applications scientifiques et techniques en défense et sécurité, notamment dans le domaine du renseignement, de la surveillance et de la reconnaissance. On peut aussi l'employer à d'autres problèmes généraux de reconnaissance de forme, par exemple la reconnaissance des visages. Nous avons donc découvert une propriété particulière de la méthode de fusion au niveau des scores : elle impartit une valeur pratique aux données de signature de mauvaise qualité et permet de les exploiter. Notre recherche constitue un pas important pour la mise au point d'algorithmes d'identification des objectifs.

Perspectives: Jusqu'à maintenant, nos recherches n'ont porté que sur l'application de la méthode de fusion des scores à l'analyse de l'identification des signatures d'objectifs par radar. Pour ce rapport, nous avons analysé des signatures d'objectifs au sol dans la bande X (10 GHz) et nous avons obtenu des résultats exceptionnellement bons. Lors de travaux antérieurs, nous avions étudié les signatures d'aéronefs en vol dans la bande Ku (16 GHz) et avions également obtenu d'excellents résultats d'identifications. Les recherches sont actuellement étendues au problème de la reconnaissance des visages. Un projet de recherche, Démonstration d'un algorithme et d'un système de reconnaissance des visages sur vidéo, est en cours qui évaluera la méthode de fusion au niveau des scores, des informations contenues dans des images vidéo.

On a publié très peu de travaux théoriques sur la méthode de fusion au niveau des scores. Lui donner une description mathématique plus précise et, ainsi, un fondement théorique plus solide constituerait un défi et une occasion. Réaliser davantage de recherche fondamentale serait désirable et aurait une valeur stratégique. Une meilleure compréhension conceptuelle de ses fondements aurait un effet important pour son application à de nouvelles utilisations et à d'autres problèmes de reconnaissance de forme, particulièrement dans les domaines de la science et de la technologie en défense et en sécurité.

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1 Introduction

Over the past twenty years, an extensive research effort has been undertaken in developing algorithms for the pattern recognition problem. This endeavour is particularly relevant and important to various military and security applications. These include Combat Identification, Aided Target Recognition, Low Probability of Intercept radar identification and human biometric recognition. Up until recently, much of the effort has been devoted to achieve high identification accuracy using a single target signature as input in the identification process. The motivation behind the single-look approach is driven partially by idealistic factors. The objective of the identification problem was initially viewed as one that was dealing with the creation of a model, which given a minimum amount of input information, would be able to generate the most accurate identification decision outcome. A second factor was practical consideration. When the target identification development effort was initiated more than twenty years ago, a large number of radar target signature data was not readily available. Thus it would be sensible to develop an algorithm that requires only a minimum amount of input information, but achieving the maximum results. But it was found that single-input identification accuracy was very much dependent on the quality of the input target signatures used. The signature quality can be affected by parameters such as spatial resolution, target motion effect and various environmental factors. With sufficiently good signature quality, correct identification rate in the high eighties and low nineties percentage can be achieved readily. However in some applications, for example Combat Identification, identification accuracy better than 99% is sought.

To improve on the accuracy, multi-look fusion methods have been investigated, in which a number of signatures are used collectively to determine the identification outcome. Essentially, the fusion methods make attempts to reduce the level of uncertainty in the decision outcome by maximizing the suitable measures of evidence [1]. There have been a number of different multi-look fusion approaches reported in the radar target identification problem, and in human biometric recognition, for example, fusion at the sample-input level, feature level, score level and decision level [2-12]. Techniques such as the Majority-Vote method, the Expectation-Maximization method, and the Dempster-Schafer Rule (Theory of Evidence) are some of the more popular multi-look tools used. However, virtually all multi-look fusion identification studies reported in the literature focused on the use of relatively good quality target signatures. The objectives of these studies are essentially the same, trying to improve the correct identification rate from the high 80s and low 90s to over 99%.

With the advent of surveillance technology, a large abundance of target image data are routinely available. The ability to maximize the exploitation of a large amount of available data has become a major motivation in pursuing multi-look identification methods. However, the quality of the data generated in large volume may not necessarily be adequate to provide the desired identification performance using current techniques reported in the literature.

In this report, a different perspective on the multi-look identification problem is explored. A multi-look technique known as the score-level fusion method is investigated in this work. It will be shown that the score-level fusion method does not require good quality signature data; multiple samples of marginal quality may be used instead, but can still provide highly accurate and robust identification. A qualitative explanation is given on how high performance is achieved by this method. Limitations of the score-level fusion method are also discussed.

To demonstrate the effectiveness of the score-level fusion method, a detailed comparative study is conducted to characterize two different multi-look fusion methods. The majority-vote method and the “score-level” fusion method are investigated; their identification performance are assessed and compared. The objective of the comparative study is to highlight the practical aspects and the technical advantages of the score-level fusion method by contrasting its performance with respect to that of the theoretically well-established majority-vote method.

The majority-vote method is a well-known fusion method commonly used in many different applications in pattern recognition. It has a rigorous theoretical foundation in statistical analysis [13][14][15]. On the other hand, the “score-level” fusion method has been deployed in multi-modal biometric identification where different biometrics are fused together to extract an identification decision [12]. However, analysis of the fundamentals of this fusion method is not well documented. There is apparently very little basic research being carried out on this method so far; only a phenomenological analysis of the score-level fusion method is given in [16] [17]. Empirical characterization of the score-level method will also be given here to provide better insights and clearer understanding of this process. There are a number of variations of the score-level fusion method; the “simple-average” approach is investigated in this study. It has been found that the simple-average approach gives the best identification results in biometric studies [17] [18].

Experimental High Range Resolution (HRR) profile signatures extracted from the measured MSTAR (Moving and Stationary Target Acquisition and Recognition) ground target datasets will be used to evaluate these two fusion identification methods. HRR signatures are widely used in target recognition for moving targets [13][15]. The quality of the HRR signatures can be made to vary; this facilitates the study of the effect of data quality has on the identification results. In particular, emphasis will be on demonstrating the superior identification performance of the score-level fusion method using low quality target signature data.

2 Multi-Look Identification Methods

2.1 Bayesian Classifier

A target classifier identifies an unknown target by computing a probability value to quantify how likely the input target will match with one of many targets for which the classifier has information stored in its database. Thus the design of a classifier involves modeling the likelihood of the input sample to match information stored in the classifier, determining the criteria that will adequately distinguish the input to a given known target class and designing the identification algorithm to predict an outcome.

The Bayesian classifier will be employed in the investigation conducted here. It is a widely used classifier in pattern recognition applications with well-established principles. The problem of identification is basically one of partitioning targets into different specific types, for example: tanks, armoured vehicles and trucks etc. Ideally, this partitioning is to be arranged so that none of the deduced outcomes is ever wrong. More realistically, one would like to minimize the errors in the outcomes. Thus, the problem of identification is reduced to a problem in statistical theory. The computation of the statistical likelihood of an event is given by the Bayes rule [13],

$$P(\omega_i \mid x) = \frac{p(x \mid \omega_i)\, P(\omega_i)}{p(x)}, \tag{1}$$

where ω_i is the state of the *i-th* target (e.g., tank, armored vehicle, etc.), x is the prior given information of the targets (e.g., observed data such as HRR profiles), $P(\omega_i|x)$ is the *a posteriori* probability (i.e., the probability that the state ω_i is true given the prior information x), $p(x|\omega_i)$ is the state conditional probability density (i.e., the probability distribution function), $P(\omega_i)$ is the *a priori* probability (i.e., it represents the state of our prior knowledge about the target before we have analyzed the data) and $p(x) = \Sigma_i(p(x|\omega_i)P(\omega_i))$ in the denominator is a normalization factor.

In the identification problem, the decision to declare an unknown target x to be the known state ω_m is defined by

$$P(\omega_m \mid x) = \max_i P(\omega_i \mid x) \tag{2}$$

That is, the state of the target ω_m (i.e., a specific target type) that achieves the largest probability value is declared as the identification outcome that matches the unknown input x. This is known as the nearest-neigbour rule [13].

2.2 Majority-Vote Method

An obvious extension to the Bayesian decision making process is to identify the unknown target by assigning it to the target label that occurs most frequently among k submitted samples of the unknown target. This is the essence of the majority-vote method. The majority-vote method in fact has a rigorous mathematical foundation; it can be expressed as a binominal distribution derived from random variable analysis in probability theory [15]; i.e.,

$$P_k(\omega_m) = \sum_{n=(k+1)/2}^{k} \binom{k}{n} P(\omega_m \mid x)^n \left(1 - P(\omega_m \mid x)\right)^{k-n} \tag{3}$$

where $P(\omega_m|x)$ is the *a posteriori* probability given by Equation (2) for a single-input sample (i.e., single-look) and the indices k and n are the numbers of multi-look input samples. The bracketed quantity is the binominal coefficient. The mathematical expression given by Equation (3) is also known as the k-nearest-neighbour rule [13]. The majority-vote method is a widely used multi-look fusion method in pattern recognition applications [14]. It is a physically intuitive process that can be understood easily, and it has a very well-established theoretical background.

2.3 Score-Level Fusion Method

The score-level fusion method has already been used in multi-modal biometric identification [12]. But there is very little detailed analytical work in the literature on this method. A number of analyses of the score-level fusion method are given in [16] [17] [19]. However, they are phenomenological characterization in nature. The score-level fusion method discussed in this work takes the form of a simple Bayes average of the *a posteriori* probabilities from k input samples computed by Equation (1); no decision is computed from each input sample. The *a posteriori* probability for score-level fusion is given by,

$$P_{SLF}(\omega_i \mid x_1 \cdots x_k) = \frac{1}{k} \sum_{n=1}^{k} P_n(\omega_i \mid x_n) \tag{4}$$

The identification decision is then computed by,

$$P_{SLF}(\omega_m \mid x_1 \cdots x_k) = \max{}_i\, P_{SLF}(\omega_i \mid x_1 \cdots x_k) \tag{5}$$

It should be noted that the simple Bayes average is only one of many ways of conducting score-level fusion [12]; but it seems to provide the best performance, at least in biometric identification applications [17] [18]. A more detailed discussion from analysis using measured data will be given in Section 5. In brief, the score-level fusion method can be summarized as a form of implementing the Bayes decision rule by minimizing the classification errors over and above the Bayes rate due to errors in the estimate of the *a posteriori* probability. The larger the variance of the error distribution, the larger the classification error becomes. The score-level fusion method reduces the variance and hence diminishes the classification error [16].

3 MSTAR (Moving and Stationary Targets Acquisition and Recognition) Datasets

The performance of the majority-vote method and the score-level fusion method will be assessed using measured target signature data from the MSTAR datasets. These datasets contain measured SAR (Synthetic Aperture Radar) images of 10 ground vehicles and one man-made canonical target (SLICY), for a total of 11 targets. The details of the MSTAR datasets are tabulated in Table 1; photographs of the target types are shown in Figure 1. The SAR images were collected using the spotlight-SAR mode with an angular coverage from 1 to 360 degrees in azimuth. The SAR-image data collected at depression angles 15 and 17 degrees are used for identification analysis, one as test set and the other as library set in the classifier. Two of the targets, BPM2 (armoured personnel carrier) and T72 (battle tank), have 3 variants each; that is, there are three versions of the same target with slightly different target configurations [21]. All images have equal down-range resolution Δr_d and cross-range resolution Δr_c; that is, $\Delta r_d = \Delta r_c = 0.305$ m. Each SAR image represents an angular aperture of,

$$\Delta\theta = \frac{c}{2f\Delta r_c} = 2.9 \text{ deg}, \tag{6}$$

where $f = 9.6$ GHz is the centre frequency of the radar waveform and c is the speed of light. The spotSAR radar was flown several times around the targets, providing multiple 360-degree azimuth coverage in the MSTAR measurements.

Table 1 Target types in the MSTAR data set used in the identification analysis

Target types	No. SAR images Test set (15 deg. elevation)	No. of SAR images Library set (17 deg. elevation)	Pixel size of SAR images	No. of valid HRR signatures yielded per SAR image [14]
BMP2(9563)	195		128x128	96
BMP2(9566)	196		128x128	96
BMP2(c21)	196	233	128x128	96
T72(132)	196	232	128x128	96
T72(812)	195		128x128	96
T72(s7)	191		128x128	96
BTR70	196	233	128x128	96
BTR60	195	256	128x128	96
BRDM2	274	298	128x129	96
ZSU	274	299	158x158	120
T62	273	299	172x173	136
ZIL	274	299	192x193	152
2S1	274	299	158x158	120
D7	274	299	177x177	136
SLICY		274	54x54	48

Figure 1 Photographs of the ground-vehicle targets from the MSTAR datasets.

3.1 Extracting High Range Resolution profiles as signatures

High Range Resolution (HRR) profiles as target signatures can be extracted from the MSTAR SAR images [20]. The amplitudes of the extracted HRR profiles from the SAR images can vary considerably with changing azimuth angle. HRR-profile signatures of different qualities can hence be generated by averaging a number of HRR profiles over different subtended azimuth aperture sizes [20]. The fluctuation in the amplitude as a function of the azimuth angle is a well-known phenomenon [22]; it is known as the glinting effect in which the phases of two or more scatterers residing in the same range bin interfere with one another as the azimuth angle is rotated slightly. It has been reported that the fluctuation can be mitigated effectively by averaging the HRR profiles over a large azimuth angle [11][23]. Hence four sets of HRR signatures of different qualities are created by extracting 8, 4, 2, and 1 averaged HRR profiles from each SAR image. These correspond to signatures subtending an azimuth aperture of 0.36, 0.73, 1.45 and 2.9 degrees respectively.

Figures 2 and 3 show sequences of 4 sets of HRR signatures of different qualities for the BMP2 armoured personnel carrier and the T72 battle tank respectively. It can be seen that the HRR profile-to-profile variability is very large when the azimuth angle subtended is small; i.e., when 8

HRR profiles are extracted from 1 SAR image. This is illustrated in Figures 2a and 3a. As the subtended azimuth angle is increased in averaging the HRR profiles, the profile-to-profile variability subsides progressively. This is illustrated in Figures 2c and 3c (i.e., 2 HRR profiles created from 1 SAR image). When a HRR profile is generated by averaging over the whole SAR image (2.9 degrees in azimuth), the amplitude fluctuations in the averaged HRR profiles have subsided very considerably such that the HRR profiles between adjacent SAR images look very similar. This is illustrated in Figures 2d and 3d. Thus, the quality of the signatures can be characterized qualitatively by the amount of variation from profile to profile in the HRR signatures, as illustrated in Figures 2 and 3. In Section 4.4, a more quantitative characterization of the quality of target signatures will be given; it will be shown that the correct identification rate is dependent on the amount of profile-to-profile variability in the HRR signatures.

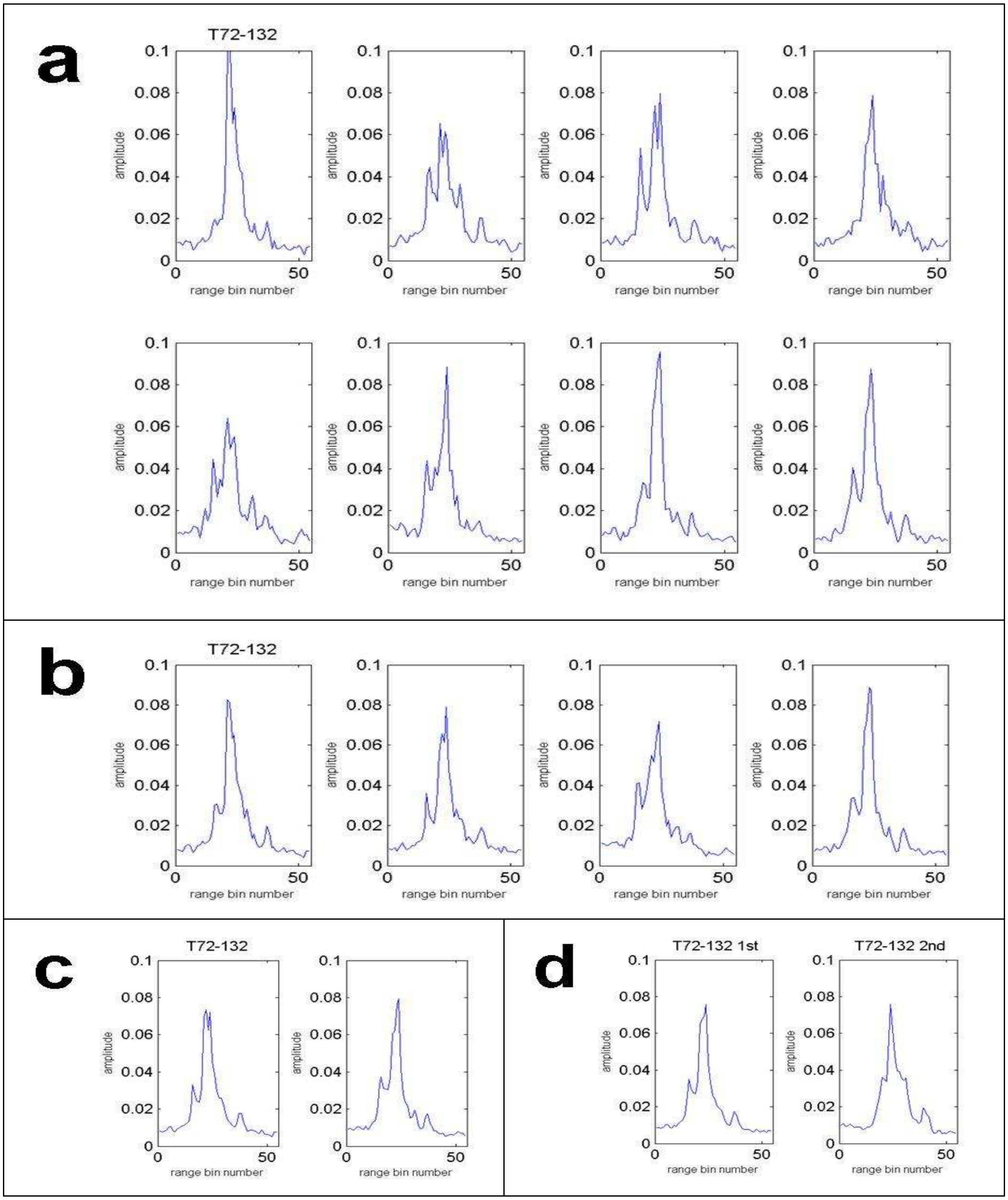

Figure 2 HRR profile variability as a function of azimuth angle subtended for the T72 battle tank. Each HRR profile is averaged over: a) 0.36 degrees, b) 0.73 degrees, c) 1.45 degrees, d) 2.9 degrees in azimuth angle. In d), averaged HRR profiles from 2 adjacent SAR images are shown.

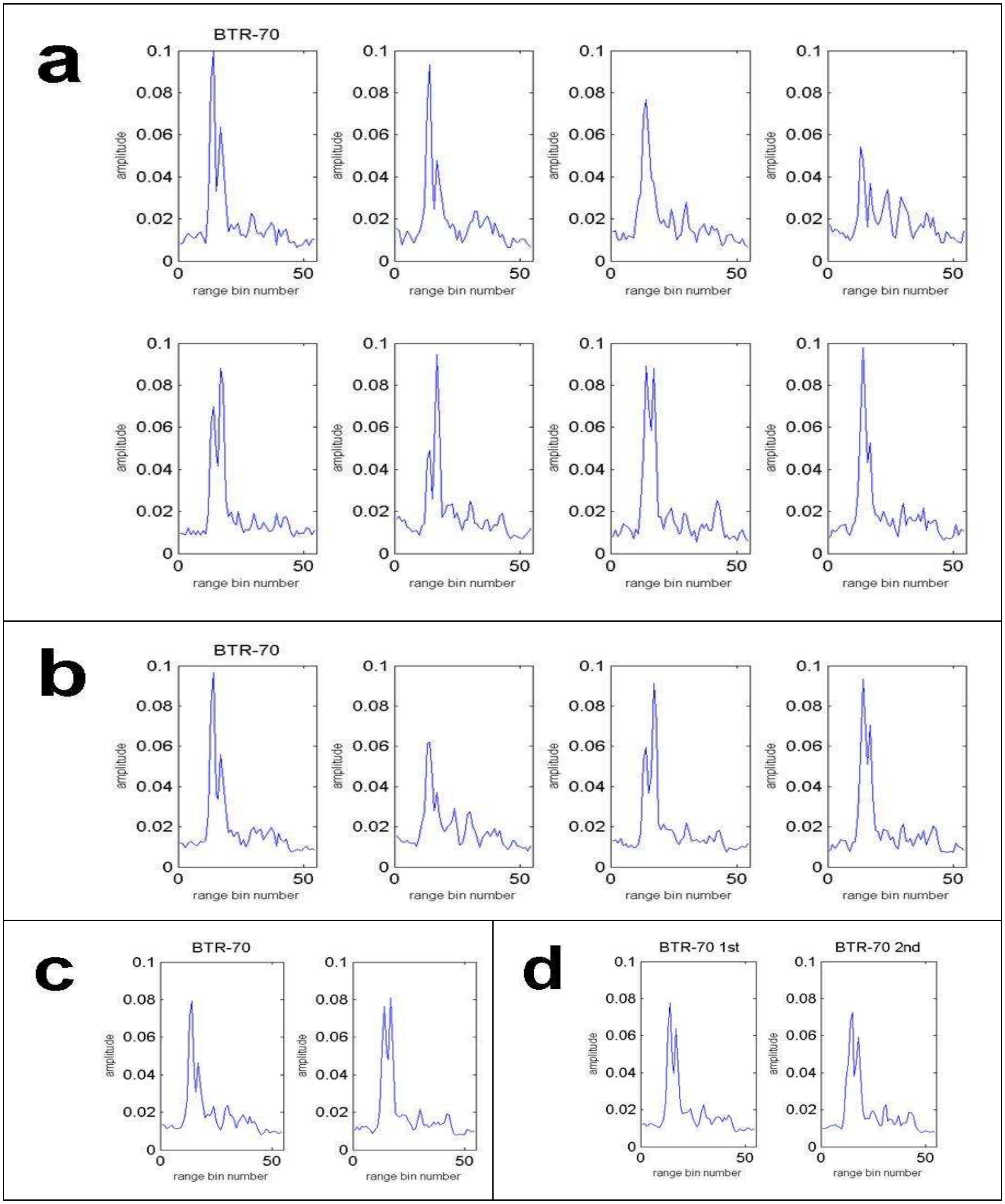

Figure 3 HRR profile variability as a function of azimuth angle subtended for the BTR70 armoured carrier. Each HRR profile is averaged over: a) 0.36 degrees, b) 0.73 degrees, c) 1.45 degrees, d) 2.9 degrees in azimuth angle. In d), averaged HRR profiles from 2 adjacent SAR images are shown.

4 Target Identification

The identification process will be computed using the Bayesian classifier described in Section 2.1. To generate an algorithm for computing the decision outcome, Bayes rule given by Equation (1) can be rewritten as [24],

$$P(\omega_t \mid x) \propto p(x \mid \omega_t). \quad (7)$$

This is because $p(x)$ in the denominator of Equation (1) is simply a normalization constant. Furthermore, in typical pattern recognition problems, we assume a uniform *a priori* probability $P(\omega_t)$. This means the unknown target is assumed equally likely to be any one of the possible targets in our knowledge. Therefore, $P(\omega_t)$ in Equation (1) is identical for all unknown input targets and it is just a constant. Thus according to the Bayes rule, the *a posteriori* probability $P(\omega_i|x)$ which provides the identification decision about the unknown target is reduced to computing the probability distribution function, $p(x|\omega_t)$ as given in Equation (7). However, in most pattern recognition analysis, there is not enough information from the data to determine a probability distribution function with well-defined parameters. In most cases, it has been found that probability distribution functions that do not make any assumption about the underlying statistical distribution can be estimated [13][25]. The probability distribution function that is of great importance and usefulness is the Gaussian distribution,

$$g(\mathbf{x}) = \frac{1}{|\mathbf{\Sigma}|^{1/2}\,(2\pi)^{n/2}} \exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T \mathbf{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu}) \right), \quad (8)$$

where $\mathbf{x}$ is a signature vector (n dimensions), $\boldsymbol{\mu}$ is the mean signature vector (n dimensions), $\mathbf{\Sigma}$ is the covariance matrix (n x n dimensions), $|\mathbf{\Sigma}|$ is the determinant and the superscript T denotes transpose of a vector. In the context of the HRR-profile analysis, the vector $\mathbf{x}$ is the input unknown HRR profile with n range bins, $\boldsymbol{\mu}$ is the library reference HRR profile in the classifier. The Gaussian distribution function is a reasonable assumption and it satisfies the Central Limit Theorem [25] which states that the sum of independent distributed random variables, under very general conditions, has a distribution converging to the normal distribution function as given by Equation (8). Furthermore, it is assumed that the features in a HRR profile are statistically independent; that is, the scattering peaks located at different range bins are independent from one another in the formation of the HRR profile [26]. With the assumption of statistically independent features within a signature vector (e.g., a HRR profile), all the off-diagonal elements of the variance $\mathbf{\Sigma}$ are zero and the diagonal elements are a constant [13]. As a result, the quadratic factor in Equation (8), $(\mathbf{x}-\boldsymbol{\mu})^T(\mathbf{x}-\boldsymbol{\mu})$, is the principal factor emerging from the Gaussian distribution function that forms the basis of a target classifier; it is known as the minimum distance classifier.

4.1 Cross-correlation Bayesian classifier

To classify an unknown input vector $\mathbf{x}$, the Euclidean distance $\|\mathbf{x}-\boldsymbol{\mu}\|$ from $\mathbf{x}$ to each of the mean vectors $\boldsymbol{\mu}$ in the classifier's library is computed. The mean vector $\boldsymbol{\mu}$ belonging to target class t that produces the shortest Euclidean distance with the unknown vector $\mathbf{x}$ is then assigned as the identified target. The cross-correlation procedure is one of many ways of working with the minimum distance classifier. This can be seen by expanding the quadratic factor in Equation (8),

$$(\mathbf{x}-\boldsymbol{\mu})^T(\mathbf{x}-\boldsymbol{\mu}) = \mathbf{x}^T\mathbf{x} - 2\boldsymbol{\mu}^T\mathbf{x} + \boldsymbol{\mu}^T\boldsymbol{\mu}\,. \tag{9}$$

The cross-correlation is then given by,

$$C = \boldsymbol{\mu}^T\mathbf{x} = \sum_n \boldsymbol{\mu}(n)\,\mathbf{x}(n)\,. \tag{10}$$

Note that if the cross-correlation coefficient, *C* is maximized (that is, maximum overlap between the vectors **x** and $\boldsymbol{\mu}$), then $(\mathbf{x}-\boldsymbol{\mu})^T(\mathbf{x}-\boldsymbol{\mu})$ in Equation (9) is minimized. A normalized form of the cross-correlation procedure is given by the Cauchy-Schwartz Inequality [13],

$$C(\mathbf{x}(m),\boldsymbol{\mu}) = \frac{\sum_n \left(\mathbf{x}(n-m)\,\boldsymbol{\mu}(n)\right)}{\left(\sum_n \mathbf{x}(n)^2\right)^{1/2}\left(\sum_n \boldsymbol{\mu}(n)^2\right)^{1/2}} \le 1\,. \tag{11}$$

The variable *m* is a shifting parameter for sliding one vector over the other to maximize the cross-correlation coefficient *C*. This normalized form of the cross-correlation method is used in the identification analysis here.

In the cross-correlation process, the unknown input HRR profile, **x** is correlated with respect to the library templates $\boldsymbol{\mu}_{t,i}$ to find the maximum cross-correlation response within each target class t; i.e.,

$$R(\mathbf{x},\boldsymbol{\mu}_t) = \max_i(C(\mathbf{x},\boldsymbol{\mu}_{t,i}))\,. \tag{12}$$

The subscript *i* denotes the *i-th* library template in target class *t*. There are *N* templates in each target class covering target azimuth from 0 to 360 degrees ($i = 1, \ldots, N$). Correlation of the input test signature against all *N* templates in each target class *t* is carried out, and this is repeated for all target classes in the classifier. A set of $R(\mathbf{x}, \boldsymbol{\mu}_t)$ values is then created, one value for each target class *t*. Finally, to determine the identification of the test input signature, a search for the maximum cross-correlation response $R(\mathbf{x}, \boldsymbol{\mu}_t)$ among all target classes is conducted. The target class label T that corresponds to the maximum correlation response is assigned as the identified target class for the test input,

$$\mathrm{T} = \arg(\max_t R(\mathbf{x},\boldsymbol{\mu}_t))\,. \tag{13}$$

4.2 Extended Operating Conditions

In order to make decisions that are meaningful in the identification analysis, realistic conditions must be incorporated in the identification process. The Extended Operating Conditions (EOC) are a set of rules that allow the testing of the target classifier under more realistic real-world scenarios. They are defined as operating conditions that differ significantly from the trained conditions of the classifier [21][27]. This allows more rigorous tests to be conducted to assess the identification algorithm. The EOCs as outlined in references 21 and 27 are applied here in examining the identification algorithm's performance. The extended operating conditions are listed as follows:

1. Data measured at 17-degree depression angle are used as library data in the classifier, and data at 15-degree depression angle are used as unknown inputs for testing (that is to say, identification is performed using data that are "away from the trained" conditions).
2. No knowledge of target aspect information of the unknown test inputs is assumed. Identification evaluation is performed over 360 degrees in azimuth. In other words, the algorithm must be able to handle an ambiguous target pose.
3. Only one variant of the BMP2 (armoured personnel carrier) and one variant of the T72 (battle tank) are included as the library database in the classifier. Three variants of the BMP2 and three variants of the T72 are used as unknown test targets (see Table 1).

A 11-class forced-decision classifier is used to provide a comparison of the identification performance between the majority-vote method and the score-level fusion method.

4.3 Random aspect input signature sampling

As discussed in Section 3, the MSTAR datasets were collected at all azimuth aspects; i.e., covering 360 degrees. An example of the azimuth distribution of the MSTAR data collected for the BTR70 (armoured personnel carrier) is shown in Figure 4a. Random sequences of the test input signatures in azimuth are selected for identification analysis; an example of a randomized azimuth sequence is illustrated in Figure 4b.

The random selection of azimuth aspects permits more realistic and flexible conditions to be analyzed in the identification process. For example, real-world data could be collected from multi-platform sensors that are distributed over a wide area spatially or from an accumulation of data by a single sensor collected over an extended period of time during a long surveillance mission [9]. Thus, any available data spanning over a large azimuth region due to spatial diversity or temporal diversity can be utilized.

Technically, the random azimuth selection of the input test samples is also consistent with the underlying assumptions used in the identification analysis. For example, the Gaussian distribution used in the Bayesian classifier, Equation (8), implicitly implied a random sampling process, and the majority-vote method is based on random sampling statistics. Hence, the random-aspect signature sequence used in multi-look sampling is a logical choice and provides a consistent, valid basis for the multi-look identification analysis.

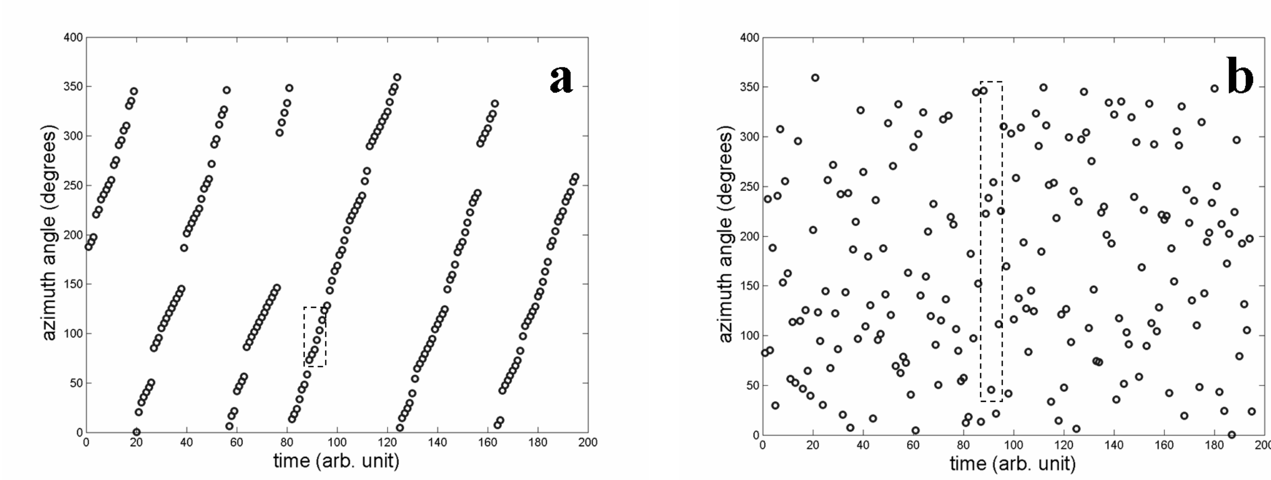

Figure 4   Examples of a) a multi-look sequence from consecutive aspect angle data as taken in the MSTAR measurements, b) a multi-aspect sequence (dashed box) from randomized aspect angle data.

4.4 Quantifying the quality of the HRR-profile signatures

In Section 3.1, the quality of the HRR-profile signature data is characterized qualitatively by the profile-to-profile variability. Intuitively, it is expected that better the data quality, more accurate the identification would be. Thus, the correct identification rate can be used as an indicator for assessing the signature quality. Using the Bayesian classifier and procedures described in Sections 4.1, 4.2 and 4.3, the quality of the HRR signature datasets can be characterized more quantitatively from the identification results.

Single HRR signature is used as unknown input into the Bayesian classifier; an identification is made for each test input signature. In the identification process, the qualities of the signatures in the test set and in the classifier library are the same; that is to say, the test set and the train set are consistent and compatible with each other. Figure 5 shows the correct identification rate as a function of the signature quality expressed in terms of the subtended azimuth angle of the HRR profiles. It can be seen that as the quality of the signature improves, the correct identification rate increases as a result. The correct identification rate is defined as the ratio the number of correctly identified input signatures to the total number of signatures tested. Table 2 shows the identification results in the form of a confusion matrix for the signature set that has the poorest quality, e.g., the HRR signatures with the smallest subtended azimuth angle (0.36 degrees). The correct identification rate P_{id} in this case is only 37%, or 9581 correct identifications out of 25624 input signatures tested. Figure 5 provides a summarized view of the effect of the quality of the data on the identification process. It is also seen from Figure 5 that even for the best quality data case, the quality is still not adequate enough to achieve high accuracy; the correct identification rate achieved is only 72%. This underscores the short-coming of the single-look approach and motivates the investigation into multi-look identification procedures.

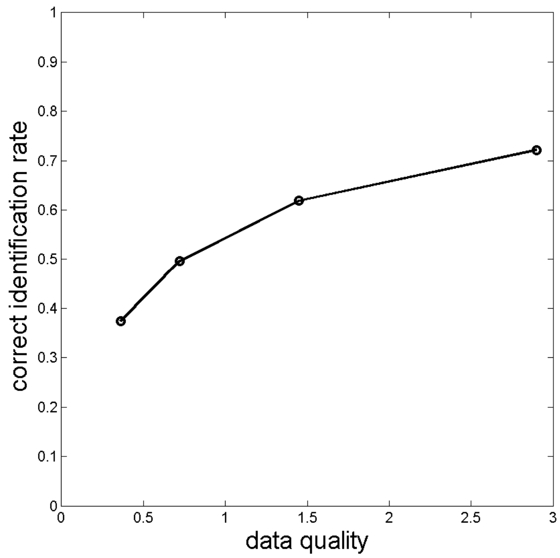

Figure 5 Correct identification rate P_{id} as a function of data quality.

Table 2 Single-look identification results from a 11-class classifier for the dataset with the poorest target signature quality

Library	MP2 (c21)	T72 (132)	BTR70	SLICY	BTR60	BRDM2	ZSU	T62	ZIL	2S1	D7
Test targets											
BMP2(9563)	**554**	143	188	21	184	195	26	33	81	117	18
BMP2(9566)	**503**	139	171	22	232	237	24	21	69	127	23
BMP2(c21)	**550**	171	167	18	167	177	21	53	83	125	36
T72(132)	132	**554**	63	7	97	57	107	95	189	146	121
T72(812)	107	**381**	54	5	84	83	107	164	193	178	204
T72(s7)	143	**378**	75	17	180	98	136	93	163	162	83
BTR70	190	53	**640**	0	193	246	13	30	49	136	18
BTR60	131	172	158	2	**448**	152	57	88	142	153	57
BRDM2	260	95	331	20	241	**949**	25	26	86	133	26
ZSU	13	90	5	10	27	9	**1275**	196	183	117	267
T62	64	168	30	23	142	59	388	**733**	231	107	239
ZIL	91	208	67	20	130	87	197	162	**818**	204	208
2S1	175	208	114	12	139	96	137	188	182	**798**	143
D7	21	75	10	28	58	13	335	323	176	153	**1000**

total no of test inputs = 25624
no of correct ID = 9581
correct ID rate = 0.3739

5 Identification Results: Majority-Vote vs. Score-Level Fusion

Over the past 10 years or so, the biometrics community has been working on the identification problem using various multi-look fusion schemes to combine different biometric information in the identification process, e.g., face images, fingerprints, hand geometry, voice patterns and iris scans. There are generally four different multi-look fusion approaches: sample-level, feature-level, score-level and decision-level fusions [9]. Sample-level fusion combines a number of target signatures or images together; this is illustrated in Figure 6a. To a certain extent, a sample-level fusion has already been applied in the non-coherent averaging of the HRR profiles in Section 3.1 to generate the different grades of signature quality by varying the profile-to-profile variability. It can be seen from Figure 5 that improvement in the correct identification rate can indeed be achieved by fusing a number of samples together. Feature-level fusion involves extraction of relevant information from the target signatures. The set of extracted features are then used as input parameters in the identification process; this is illustrated in Figure 6b. In target identification analysis using HRR profiles as target signatures, the normal practice is to use the whole HRR profile as a target feature; hence feature-level fusion is not used.

In this section, a comparative study is conducted to evaluate the performance of the two remaining multi-look identification methods, majority-vote fusion and score-level fusion. The results from each of these two methods will be discussed and compared. The advantages of using the score-level fusion method will then be assessed quantitatively. It will be shown that the score-level fusion method is the more accurate and versatile of the two, and this method has a significant practical implication in applications.

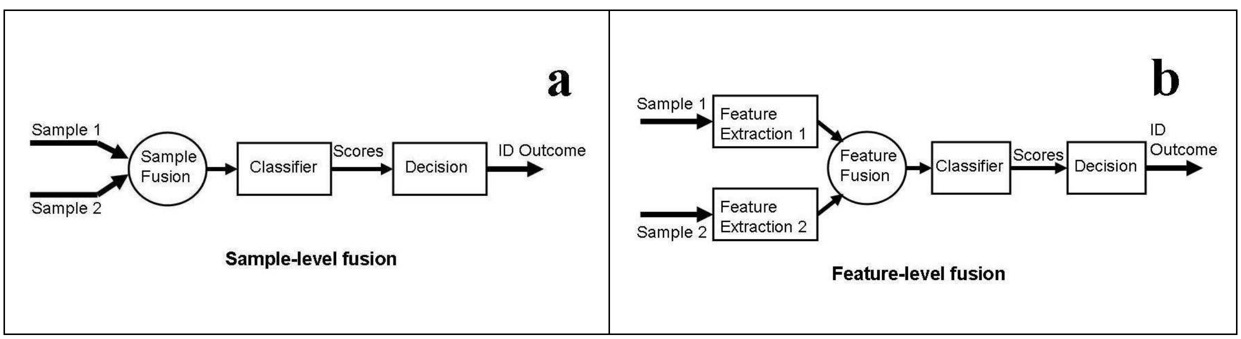

Figure 6 Schematics of the sample-level (a) and feature-level (b) fusion methods

5.1 Majority-Vote Method

The majority-vote method is a data fusion procedure that makes a decision through consensus from multiple outcomes at the decision level of the classifiers; this is illustrated schematically in Figure 7a. An identification outcome from each single test sample in a multi-look sequence is first computed using Equation (13). Given a sequence of k input unknown signatures, there are k

target labels as identification outputs. The majority-vote method simply finds the target label that appears the largest number of times in the k-multi-look sequence. It should be noted that an odd number of multi-look samples is usually used in majority-vote; this is to ensure that a tie will be avoided in the vote counts. A minimum majority is required to declare a decision; the minimum majority n is given by $n = (k+1)/2$. As an example, if $k = 7$, then the minimum number of votes needed to declare an identification is $n = 4$. If $n < 4$, then a "no-majority" response is given as output. Note that a no-majority response is counted as incorrect identification in the majority-vote evaluation carried out in this study.

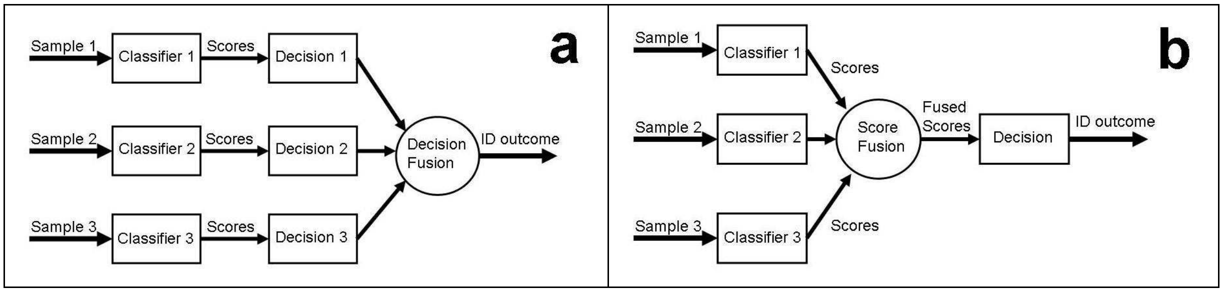

Figure 7   Schematics of the majority-vote (a) and score-level (b) fusion methods.

Figure 8 shows the majority-vote identification results from measured data (dashed curves) as a function of the number of signatures used in a multi-look sequence from an 11-class target classifier. The top dashed curve corresponds to results from the dataset with the best signature quality; the bottom dashed curve represents results from the dataset that has the poorest signature quality. There are a number of notable results that can be deduced from Figure 8.

For data quality that is good enough to achieve a correct identification rate P_{id} of greater than 50% in single-look input (k =1), the majority-vote identification results improve quite considerably with an increasing number of signature samples in the multi-look sequence. These are illustrated by the upper two dashed curves in Figure 8. As the data quality deteriorates to such levels that the correct identification rate is below 50%, an increase in the number of multi-look samples does not improve the correct identification rate. In fact, the identification results are worse using the majority-vote method. These are shown in the two lower dashed curves.

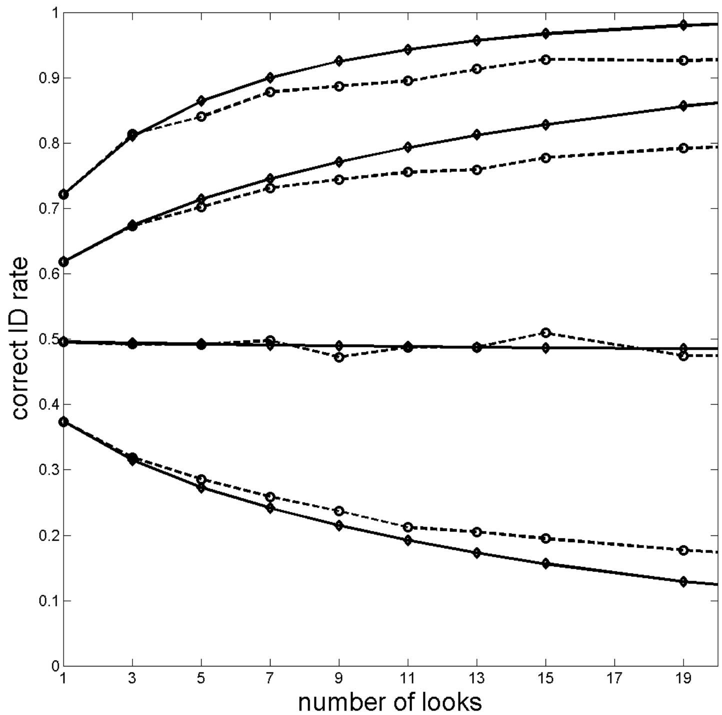

Figure 8 Majority-vote identification results. Correct identification rate, P_{id} as a function of the number of samples, N in the multi-look sequence for 4 different signature data qualities. Solid curves = theoretical predictions; dashed curves = measured data.

The majority-vote method has a rigorous theoretical background; it can be described by a mathematical formula as given by Equation (3). These predictions are given by the solid curves in Figure 8. The majority-vote results obtained from measured data (dashed curves) are compared with the theoretical predictions (solid curves). It can be seen from Figure 8 that the difference in the correct identification rate is less than 6% between the measured results and the theoretical predictions in all 4 cases. This indicates that the results from the measured data are reasonable in providing a validation of the notion of different signature qualities among the 4 datasets. Furthermore, these results reveal a serious limitation of the majority-vote method; its performance is seen as being constrained by the quality of the target signatures. The results in Figure 8 suggest that in order for the majority-vote method to be useful, the quality of the target signatures must be good enough to achieve a single-look correct identification rate of at least 70% or better. Otherwise, correct identification rate of greater than 90% may not be realizable.

5.2 Score-Level Fusion Method

The score-level fusion method combines the cross-correlation scores from multiple Bayesian classifiers as described in Section 4.1. That is to say, the cross-correlation score from each input sample is computed, but no identification decision is made. The cross-correlation scores from k input samples are instead combined using Equation (4) to generate a single effective score for each target class that are stored in the classifier. Then, an identification decision is made by finding the target label that has the largest score as given by Equation (5). A schematic of the score-level fusion process is shown in Figure 7b. Using Equation (4), a simple-average cross-correlation score from a series of k input HRR signatures is computed for each target class t in the classifier; i.e.,

$$\langle R_t \rangle = \frac{1}{k} \sum_{n=1}^{k} R(\mathbf{x}_n, \boldsymbol{\mu}_t), \tag{14}$$

where $R(\mathbf{x}_n, \boldsymbol{\mu}_t)$ is the maximum cross-correlation response for each of the test inputs $\mathbf{x}_n$, $n = 1, \ldots, k$ as given by Equation (12). This procedure is repeated for all target classes in the classifier, e.g., $t = 1, \ldots, 11$ in the 11-target classifier. The identification outcome is then determined by the target class label T that corresponds to the maximum multi-look response value; i.e., ,

$$\mathrm{T} = \arg(\max_t \langle R_t \rangle). \tag{15}$$

5.3 Score-Level Fusion identification results

Using the above procedure, identification results using the score-level fusion method are shown in Figure 9 given by the solid curves. It can be seen that the identification results for the 4 different signature qualities are exceedingly good when a sufficiently large number of multi-look samples is used. For comparison, the results from the majority-vote method are also plotted (dashed curves) in Figure 9. It is seen that the score-level fusion method is significantly better than the majority-vote method in identification performance for all four signature qualities. It is of particular interest to note that the correct identification rate using poor quality signature can be improved very dramatically, from 37% in single-look to over 97% using a large number of look samples (>20). This is highlighted by the heavy solid curve in Figure 9. The good identification performance of the score-level fusion method has some interesting implications. Firstly, the results suggest that quantity can be used to replace quality of the data in improving the identification accuracy, e.g., using a large number of data samples of marginal quality in a multi-look sequence. Secondly, signature data of marginal quality can still be used meaningfully in target identification; this means data quality may not be as important a requirement as one would expect intuitively.

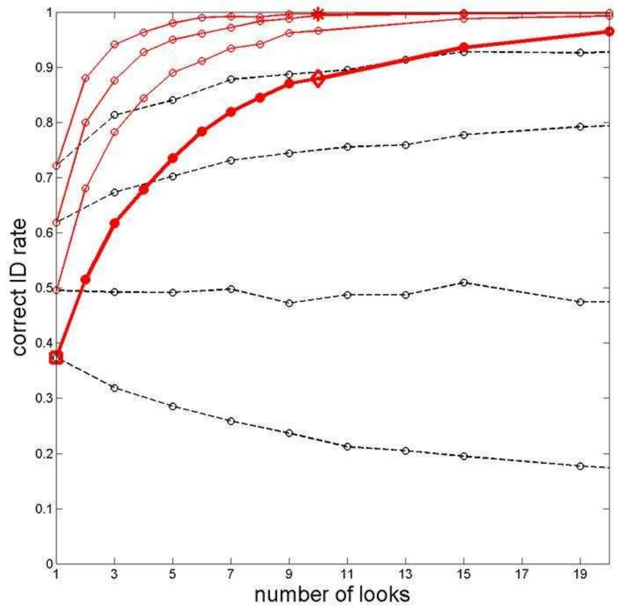

Figure 9   Score-level fusion identification results from measured data (solid curves). Correct identification rate, P_{id} as a function of the number of samples, N in the multi-look sequence. The dashed curves are the majority-vote results from measured data for comparison

6 A Qualitative Analysis of the Score-Level Fusion Method

It has already been seen in the majority-vote method that multi-look sampling can produce more accurate identification than single-look sampling. In the majority-vote case, the increase in accuracy is a consequence of the fundamental property of the binomial distribution function given in Equation (3). In more qualitative terms, the majority-vote method is expected to perform better than the best single-look classifier in identifying an unknown input target, provided that the target signature quality is sufficiently adequate. In brief, the essence of the majority-vote method is to reduce the level of uncertainty through maximizing suitable measures of evidence by monitoring how frequently a particular outcome occurs. But in the score-level fusion method, it is not clear how and why a multi-look sequence of inputs produces significantly better correct identification, even when the quality of the signatures is poor. In the limited literature available that describes the score-level fusion method, the underlying assumption is that the *a posterior* probability is affected by its associated variance [16][17]. The larger this variance, the larger the identification error is produced as a result. The score-level fusion method reduces this variance and consequently, diminishes the identification error. In other words, the target label error from the score-level fusion will be smaller than the target label error from single-look identification.

6.1 Physical characterization of the Score-Level Fusion method

In an attempt to understand more clearly why the score-level multi-look sequence produces significantly better identification results than the single-look input, it is helpful to examine the mean and standard deviation (i.e., the square root of the variance) of the quantity $\langle R_t \rangle$ as defined by Equation (14). The standard deviation is defined as,

$$\sigma_k = \left[\frac{1}{M} \sum_{n=1}^{k} \left(R(\mathbf{x}_n, \boldsymbol{\mu}_t) - A_t \right)^2 \right]^{1/2} \tag{16}$$

where A_t is the overall mean value of the maximum cross-correlation response $R(\mathbf{x}, \boldsymbol{\mu}_t)$ from a large set of test samples examined for target t before partitioning into single-look and multi-look sequences; i.e.,

$$A_t = \frac{1}{N} \sum_{i=1}^{N} (R(\mathbf{x}_i, \boldsymbol{\mu}_t)). \tag{17}$$

N is a large integer. For a k-multi-look sequence, $M = (k - 1)$ if $k > 1$ and $M = 1$ if $k = 1$. It should be noted that $N >> k$; that is to say, we are analyzing the statistics of multi-look sequences using a large set of samples. Figures 10 and 11 show the graphs of the mean values (circles) for $\langle R_t \rangle$ between a test target and each of the reference targets stored in the target classifier for single-look and for a 10-look sequence respectively. They correspond to the identification cases for the square and diamond data points shown on the bottom heavy solid curve in Figure 9, respectively.

As a note, the sample size for the single-look sequences is $N = 25624$, and the sample size for the 10-look sequences is $N = 2562$.

The mean values for $\langle R_t \rangle$ in Figures 10 and 11 are plotted as a function of the target types stored in the classifier for all multi-look test sequences before the identification of the test targets are determined using Equation(15). The standard deviations are displayed as error bars. There are 14 graphs displayed in each of Figure 10 and Figure 11. Each graph represents one of the 14 different input test target types as indicated at the top of each graph. The horizontal axis on each graph corresponds to the 11 reference target types (see figure captions) that are stored in the target classifier. Note that the correct reference target type that corresponds to the test target in each graph is indicated by an arrow in each graph.

It would be insightful to examine the mean and the standard deviation of the $\langle R_t \rangle$ values for each reference target type in the classifier on each of the graphs in Figures 10 and 11. This effectively amounts to examining and comparing the behavior of the $\langle R_t \rangle$ values by monitoring how much the standard deviation (error-bar) changes around the mean (circle) as the number of test samples increases from a single look to 10 looks in the sequence. Note that the mean values for $\langle R_t \rangle$ in Figures 10 and 11 are the same, regardless of the number of samples in the multi-look sequence. This can be explained by the fact that the overall mean value of a given total number of samples N is fixed, regardless of how this number N is partitioned into multi-look sequences of different sample sizes; that is to say, whether a sequence contains 1 sample or 10 samples, the total number of test samples involved is the same and hence its overall mean value A remains unaltered. However, the telltale sign, that the sample size in the multi-look sequence plays a role in the identification process, is the reduction of the size of the error bars as the sample size of the multi-look sequence becomes bigger. This can be seen by comparing the size of the error bars of the respective graphs between single-look and 10-look as shown in Figures 10 and 11, respectively.

The reduction in the standard deviation with increasing sample size in the multi-look sequence offers an explanation in a statistical manner of the observed improvement in the identification results. As a reminder, in each of the graphs shown in Figures 10 and 11, the mean values (circles) provide a measure of similarity between the test signature and signatures of the target types stored in the target classifier before an identification is declared. Graphically, the larger the mean value for $\langle R_t \rangle$, the more probable that the input test target would be identified as that target type. It may be easier now to see that when the standard deviation around the mean value is large, as in the single-look case in Figure 10, there is a bigger chance statistically that the test input may not be correctly identified because the $\langle R_t \rangle$ values for some incorrect reference target types in the classifier may have a larger value than the actual correct target type within the larger error margin as indicated by the error bar. As the number of test samples is increased to 10 in the multi-look sequence (Figure 11), the error bar becomes much smaller. It can be seen from Figure 11 that the $\langle R_t \rangle$ value corresponds to the correct target type is more likely to be larger than those that correspond to the wrong target types as the $\langle R_t \rangle$ values are approaching the mean values with very small errors; hence a more accurate identification can be made. In other words, it is much more likely that the reference target in the classifier with the largest mean value for $\langle R_t \rangle$ is the correct target type associated with the input test target in the 10-multi-look sequence. This is evident in Figure 11 where the correct matches are indicated by the arrows, and the mean value indicated by the arrow has the largest value in each of the graphs.

In summary, when the number of samples in a multi-look sequence is small, the averaged correlation values $\langle R_t \rangle$, between the test input and the target classes in the classifier, can vary quite considerably; i.e., having a large error-bar associated with the mean values. Hence the chance of the correlation values from the wrong target type having a greater value than the correlation value from the correct target type is greater; this translate to a lower probability of correct identification. As the number of test samples increases in the multi-look sequence, the correlation values have much less variability; i.e., much smaller error-bars associated with the mean values. Thus, the probability of making a correct identification is much higher. The mean and standard deviation of the quantity $\langle R_t \rangle$ provide a qualitative characterization of the identification results. In essence, the correct identification rate improves statistically with increasing number of test samples in the multi-look sequence because there is less error associated with the averaged correlation value $\langle R_t \rangle$.

The principle of averaging that provides a higher correct identification rate may also be used to explain why the score-level fusion method appears to be independent of the quality of the data. Figure 12 shows that the means and standard deviations for the 10-look case using the best quality signature data; i.e., the “star” data point on the top solid curve in Figure 9. Comparing Figure 12 with Figure 11, it can be seen that the mean value on the column indicated by the arrows in each of the graphs is the largest; it indicates the correct match between the input test target and the reference target. The quality of the data is reflected in the magnitude of the correlation values. The correlation values from good quality data (Figure 12) are larger than those from poorer quality data (Figure 11). But the identification decision making process is solely a problem of finding the relative maximum correlation value (i.e., Equation (15)). Relative score implies the absolute magnitude of the correlated value is not relevant. Thus, this provides an explanation as to why the correct identification outcome is independent of the data quality.

The principle of averaging is a well-tested and well-accepted concept; it is used in many real-world practical applications. Averaging is a simple procedure; often, simplicity is also associated with robustness. Thus, the “statistics of average” appears to provide a reasonable, qualitative explanation of why the score-level fusion method works so well.

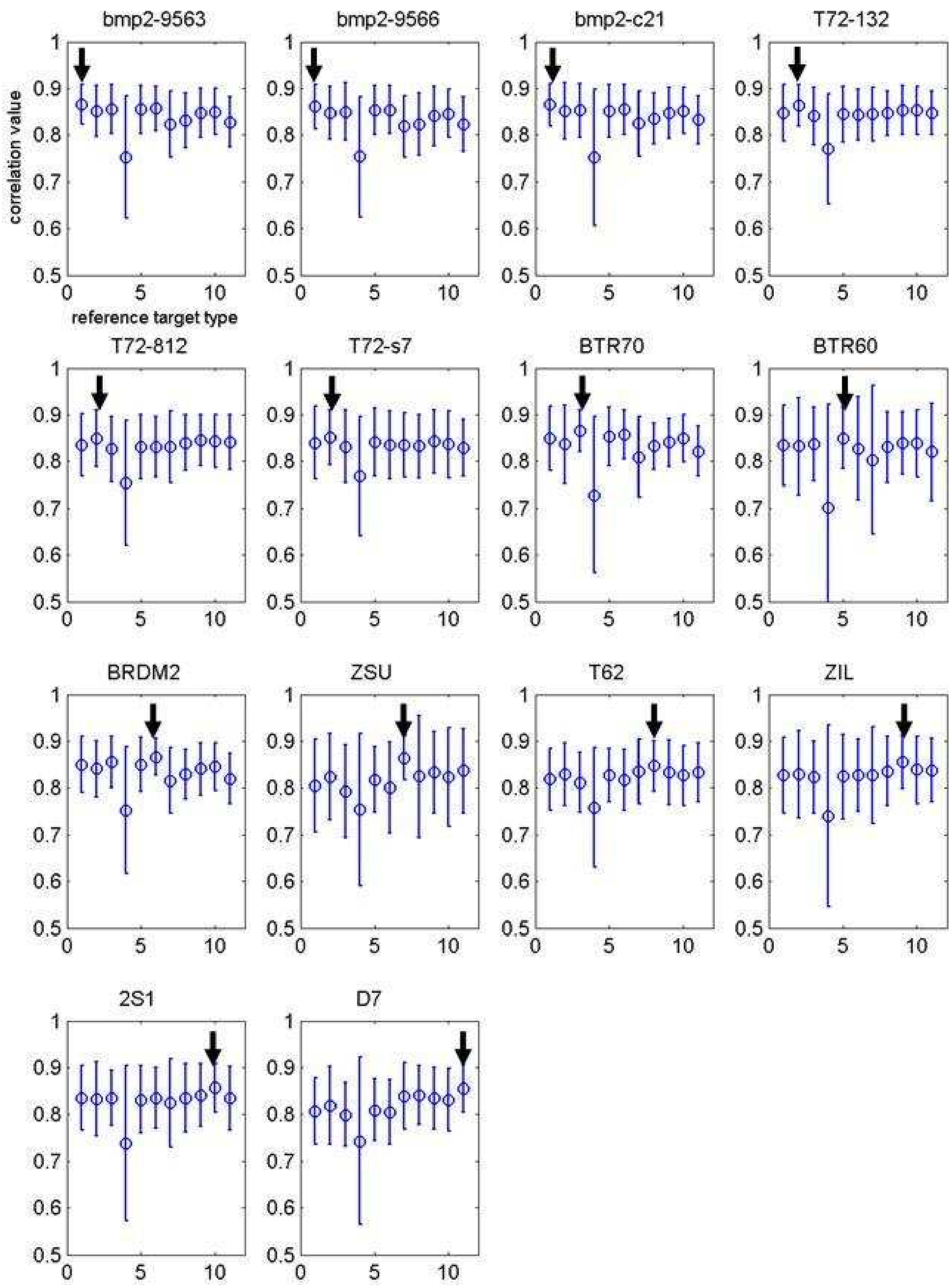

Figure 10 Means (circles) and standard deviations (error bars) for single-look using the lowest quality data set. The error bars have a magnitude of ±2 sigma. The horizontal axis on each graph represents the reference target types that are stored in the classifier: 1 = BMP2(c21), 2 = T72(132), 3 = BRT70, 4 = SLICY, 5 = BTR60, 6 = BRDM2, 7 = ZSU, 8 = T62, 9 = ZIL, 10=2S1, 11=D7. The arrows indicate the correct target types stored in the classifier that are associated with the test input target types.

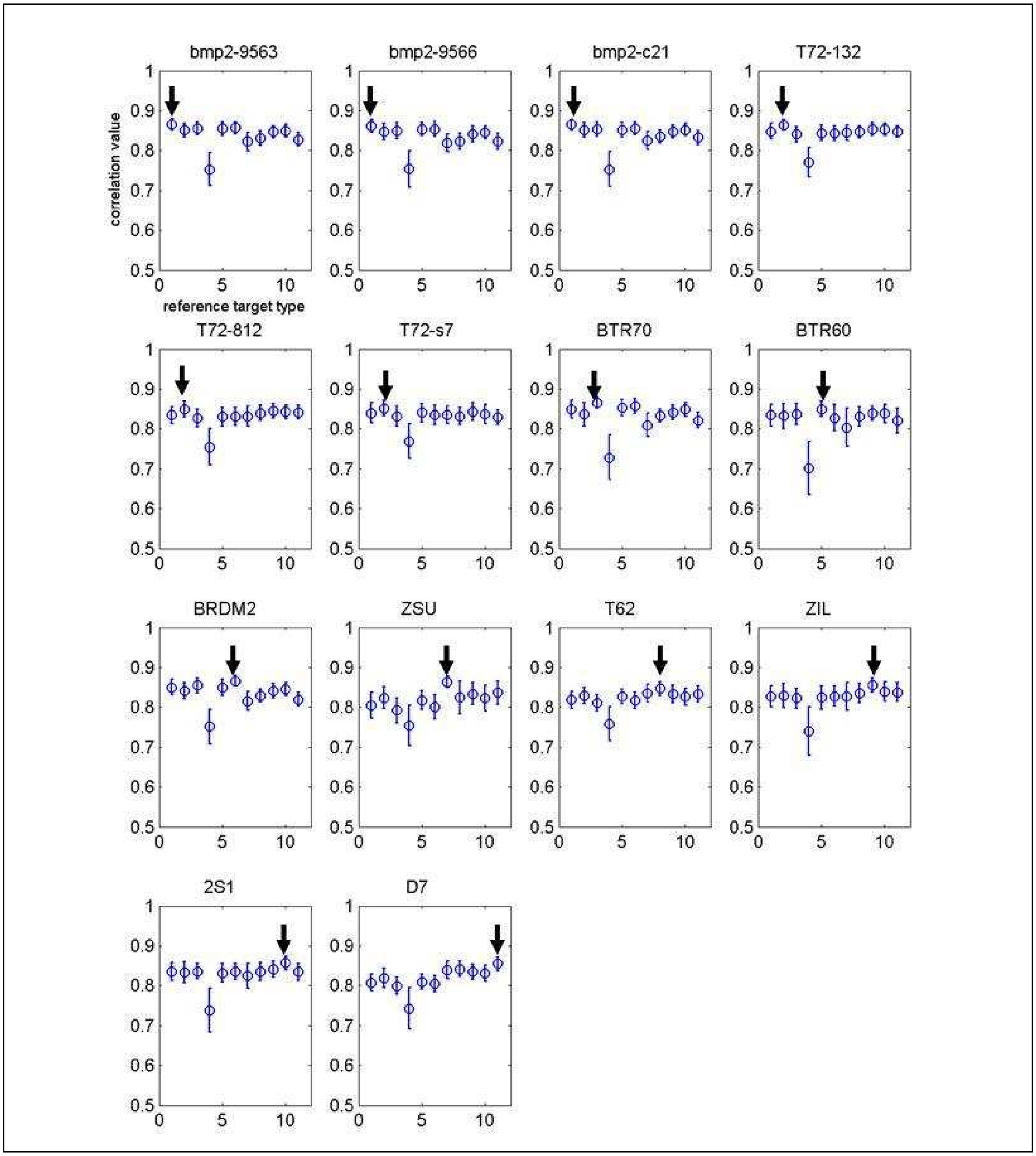

Figure 11 Means (circles) and standard deviations (error bars) for 10-look using the lowest quality data set. The error bars have a magnitude of ±2 sigma. The horizontal axis on each graph represents the reference target types that are stored in the classifier: 1 = BMP2(c21), 2 = T72(132), 3 = BRT70, 4 = SLICY, 5 = BTR60, 6 = BRDM2, 7 = ZSU, 8 = T62, 9 = ZIL, 10=2S1, 11=D7. The arrows indicate the correct target types stored in the classifier that are associated with the test input target types.

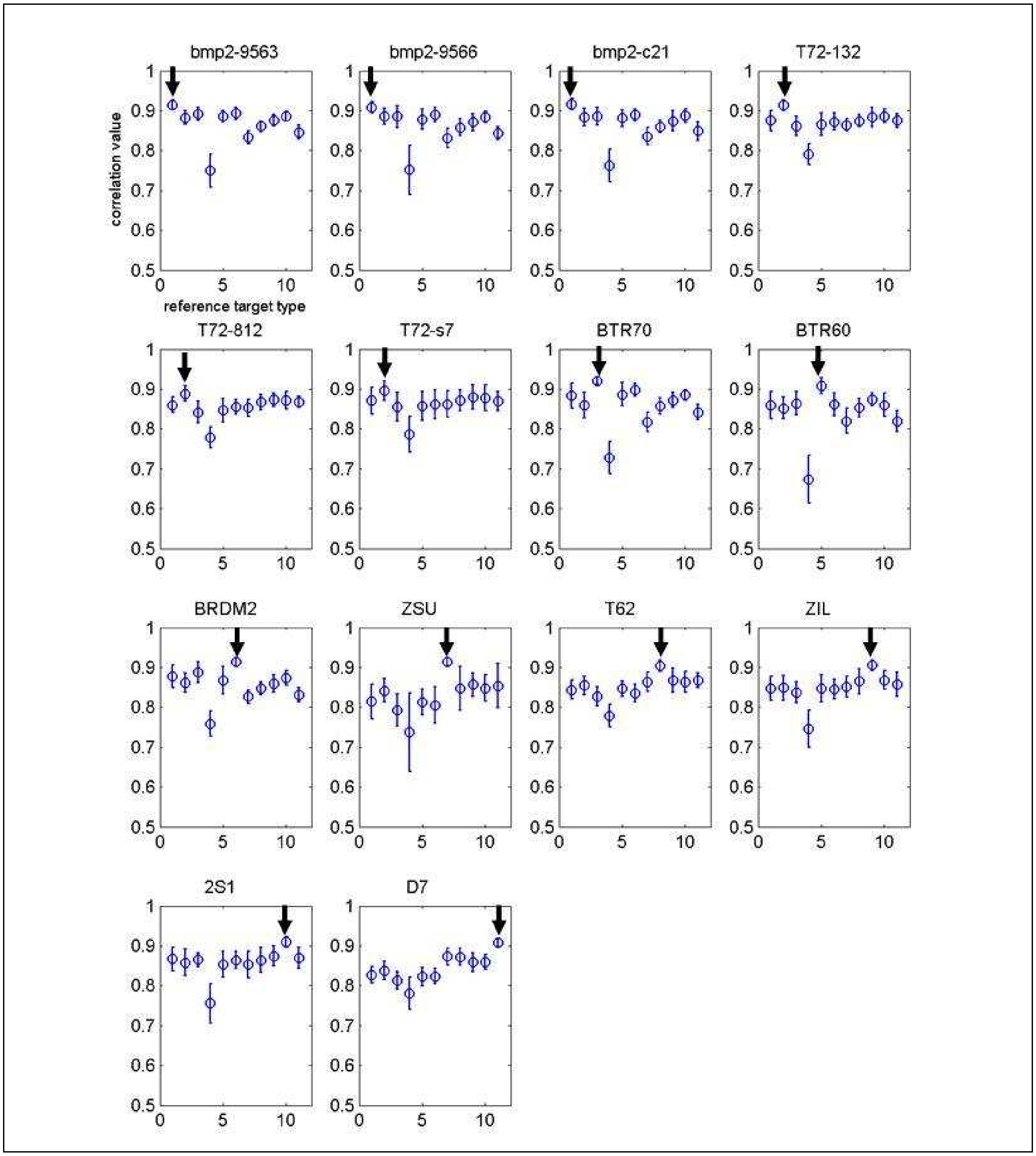

Figure 12 Means (circles) and standard deviations (error bars) for 10-look using the best quality data set. The error bars have a magnitude of ±2 sigma. The horizontal axis on each graph represents the reference target types that are stored in the classifier: 1 = BMP2(c21), 2 = T72(132), 3 = BRT70, 4 = SLICY, 5 = BTR60, 6 = BRDM2, 7 = ZSU, 8 = T62, 9 = ZIL, 10=2S1, 11=D7. The arrows indicate the correct target types stored in the classifier that are associated with the test input target types.

6.2 Empirical exponential fit to the observed results

The improvement in the correct identification rates as seen in Figure 9 using score-level fusion (solid curves) appears to be very rapid with an increase in the samples of the multi-look sequence. The rate of increase is observed to be similar and is independent of the data quality. In an attempt to quantify the characteristics of the improvement in the correct identification rate, the standard deviation (error-bar) for $\langle R_t \rangle$ is again examined to provide some extra insights; it is seen from the discussion in Section 6.1 that the correct identification rate increases as the size of the standard deviation decreases. Figure 13 illustrates the size of the error-bar as a function of the number of multi-look samples for each of the 4 different data quality cases. It is seen that the error-bar sizes are about the same for all 4 data quality cases and are found to decrease rapidly with an increase in multi-look samples.

Another perspective on the error-bar behaviour is given by normalizing the error-bars, i.e.,

$$\varepsilon_{s,N} = \frac{\sigma_{s,N}}{\sigma_{s,1}} \tag{18}$$

where $\sigma_{s,N}$ is the N-sample multi-look error-bar size, $\sigma_{s,1}$ is the single-look error-bar size and s is an index indicating the state of the data quality, e.g., s = 1, 2, 3, 4 indexing the 4 different states of data quality. The normalized error-bar size is illustrated in Figure 14a. It can be seen that the normalized error-bars are essential the same in size among the 4 data quality cases.

An empirical fitting equation to the observed identification results in Figure 9 using the normalized error bar as a parameter can be expressed as,

$$f_{s,N} = 1 - \exp\left(-q_{s,1}\left(\varepsilon_N + 0.3\right)\sigma_{s,1}N\right) \tag{19}$$

where $f_{s,N}$ is the fitted correct identification rate, N is the number of samples in the multi-look sequence, ε_N is the fitting function for the normalized error-bar size as shown in Figure 14b and $q_{s,1}$ is a fitting parameter such that the fitted single-look correct identification rate $f_{s,1}$ is matched to the measured single-look correct identification rate as an initial condition that satisfies the empirical fit in Equation (19); in other words,

$$f_{s,1} = P_{id}(s,1) \tag{20}$$

where $P_{id}(s,1)$ is the single-look value of the correct identification rate from measured data in Figure 9. This permits a common starting point for the fitting equation (Equation (19)) to be compared with the results from measured data; the comparison is shown in Figure 15a. It can be seen that the computed empirical fits (dashed curves) are in very close agreement with the measured data (solid curves). Note that in Equation (19), there is a fudge factor, 0.3 added to the normalized error-bar size variable, ε_N . The purpose of this fudge factor is to provide as good a fit as possible between the empirical fit and the measured data. The fudge factor does not have any physical interpretation or significance. The objective of the empirical fit given by Equation (19) is to provide a semi-quantitative illustration, showing that the score-level fusion method has an exponential increase in the identification performance. If the fudge factor, 0.3 is ignored, Equation (19) can be rewritten as,

$$f_{s,N} = 1 - \exp\left(-q_{s,1}\sigma_{s,N} N\right) \quad (21)$$

Since $q_{s,1}$ is just a proportional constant, the increase in the modelled correct identification rate in this case is proportional to the product $\sigma_{s,N} N$ in an exponential manner. Figure 15b shows the empirical fits given by Equation (21) (dashed curves), and a comparison with the measured results (solid curves) is made. Having the fudge factor set to 0, the empirical fits are increasing more slowly than the measured data. In either case, an exponential rise in the corrected identification rate with an increase in the multi-look samples is evident in the score-level fusion method regardless of data quality.

Thus, the score-level fusion method demonstrates that quantity can replace quality of the data to achieve good identification accuracy. However, it should be emphasized that quantity can not be expected to replace quality in an arbitrary manner. In other words, one can not arbitrarily apply quantity to replace quality and expect good identification automatically. There are two basic requirements that must be met before the score-level fusion identification can be useful. Firstly, even though the quality of the target signatures may be degraded by whatever conditions presented during data acquisition, they must possess a general resemblance that is consistent with the reference signatures deployed in the classifier's database of the same target types. Secondly, the classifier should have a robust and reliable algorithm that could give consistently a higher probability in matching the input signature to the library signature of the same target type than between dissimilar types. In other words, the use of the score-level fusion multi-look procedure may reduce the statistical fluctuation in the target matching process that causes identification errors. But the intrinsic ability of the classifier algorithm to provide correct matches of similar looking signatures is essential and is still central to the performance of a good classifier. These two basic requirements can not be expected to be replaced by multi-look procedure alone in an arbitrary manner. As discussed in Section 6.1, correct identification is achieved only if a classifier can reliably come up with the largest matching probability (i.e., correlation value) between two signatures of the same target type. Reasonable datasets, albeit large signature variability and a robust classifier, are still essential ingredients for accurate identification.

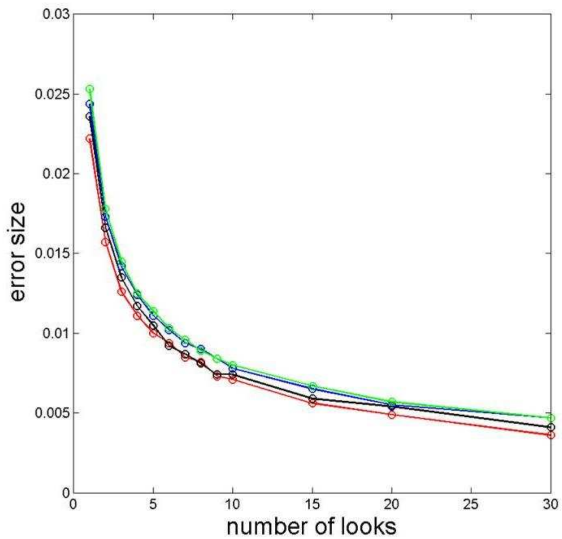

Figure 13 Error size (standard deviation) as a function of the number of multi-look samples for 4 different data quality cases.

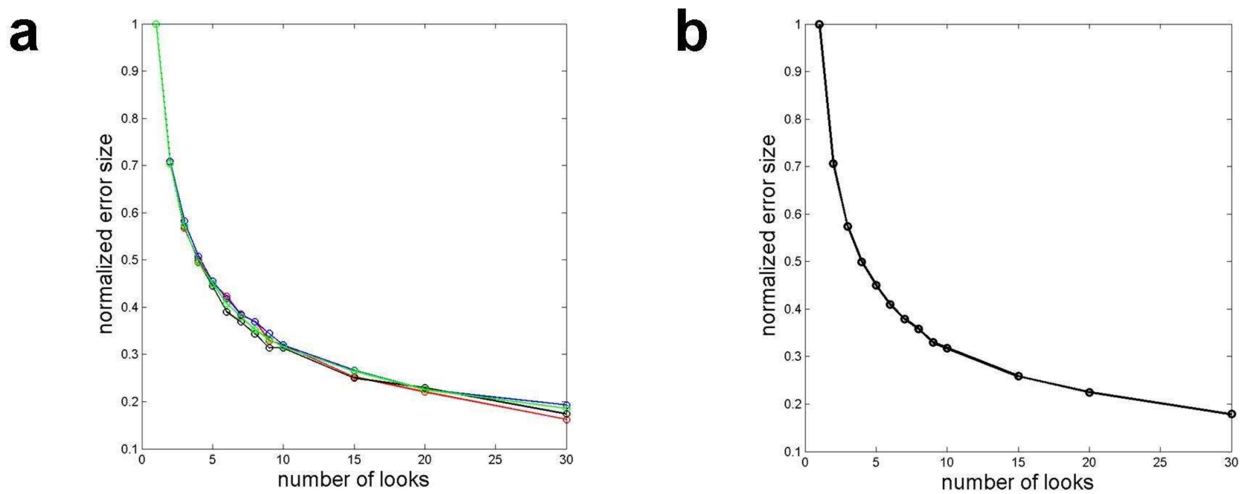

Figure 14 Normalized error size as a function of the number of multi-look samples. a) all 4 data quality cases, b) fitted normalized error size ε_N, an average of the 4 data quality cases as shown in a.

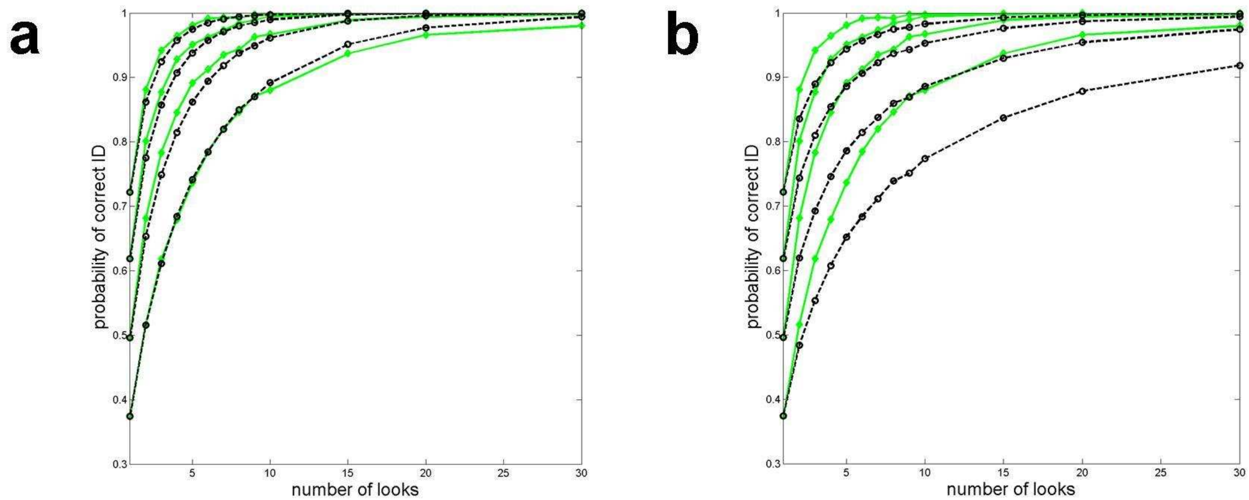

Figure 15 A comparison of the identification results between the empirical fit and the measured data. a) fudge factor set at 0.3, green solid curves = measured data, black dashed curves = empirical fit from equation (18); b) fudge factor set at 0.0, green solid curves = measured data, black dashed curves = empirical fit from Equation (20).

7 Conclusions

To remedy the inadequate performance of single-look identification, the score-level fusion method is investigated as a multi-look sampling procedure to provide highly accurate target identification performance. The concept of score-level fusion has been known for some time and the method has been deployed in multi-modal biometric identification, fusing different biometric information together to obtain more accurate identification. What is new and original in this study is the demonstration of significant improvement in the target identification accuracy using multiple samples of marginal quality signatures. The problem of improving accuracy using multiple samples of poor quality data has largely been ignored in the pattern recognition community. The study conducted in this work has presented a new and innovative perspective on target identification. A desirable characteristic has been identified in the score-level fusion process that can provide highly accurate identification using marginal quality target signatures.

The superior performance of the score-level fusion method is highlighted in a comparative analysis with the majority-vote method using experimental target signature data of varying qualities. Majority-vote is a well-established multi-look procedure. It is shown that the performance of the majority-vote method is dependent on the target data's quality. Any increase in the identification performance is insignificant when the target signature quality is marginal. When the target signatures are particularly poor in quality, the majority-vote method can not be used to improve on the identification performance at all. But on the other hand, the score-level fusion method offers very significant performance improvement, even working with poor quality data. An example is shown in which the correct identification rate improves from 37% in the single-look mode to over 97% in the multi-look mode. This is illustrated in Figure 9 (heavy solid curve). Moreover, the increase in performance is exponential as a function of the number of samples used in the multi-look sequence. This suggests that the score-level fusion method can provide an efficient means to significantly improve the identification performance, even when poor quality data are used.

The "quantity over quality" approach to exploiting data could have a notable impact in target identification applications. With the advent of sensor technology, large quantities of target data of marginal quality can be made available routinely. Whereas, collecting quality data still presents a technical challenge. Thus, the significant improvement in identification performance and the ability to maximize the exploitation of a large amount of data offer potential niche applications such as Aided Target Recognition, radar emitter identification [30] and human biometric recognition using the score-level fusion method.

A qualitative characterization of the score-level fusion method based on the statistics of average is given to explain the excellent identification results obtained in the analysis. There is very little analytical work on the score-level fusion method being reported in the literature. Given the positive results obtained in this study, it would be useful to conduct further study on the basics of this process to gain better insights. This presents a challenge and an opportunity to put the score-level fusion method in a more rigorous fundamental framework. A good conceptual understanding of the fundamental framework could have significant impact in opening up new applications to pattern recognition and identification problems, particularly in the Defence and Security S&T field.

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Single-look identification procedure using one input at a time has been the principal mode of analysis used in the target recognition community for much of the past two decades. But it has been realized that the single-look approach can only achieve modest correct identification performance and this is not adequate for many target identification applications. Furthermore, in order for the single-look procedure to perform well, good target data quality is required. In this report, a multi-look method known as score-level fusion is investigated. It permits a significant improvement in the identification performance. Moreover, it does not require good quality target signature data; multiple signature samples of marginal quality may be used instead. Results from analysis using measured radar target data have shown quantitatively that the correct identification rate can be improved very dramatically. Furthermore, the score-level fusion method is very efficient; the identification performance increases exponentially with an increase in the number of samples used in the multi-look sequence. A qualitative characterization of the score-level fusion method based on the principle of averaging is given. It provides an intuitive understanding of this fusion process and how improvement in identification accuracy is achieved. The identification results obtained in this study suggest that quantity can be used to replace quality of the data to improve target identification accuracy. This has an interesting practical implication. With the advent of sensor technologies, large quantity of data of marginal quality can be captured routinely. This “quantity over quality” approach could maximize the exploitation of available data to provide reliable and robust identification. Thus, the score-level fusion method could have the potential of being developed into a disruptive technology for target identification and pattern recognition problems.

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multi-look sampling, score-level fusion, target identification, signature quality, pattern recognition.

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