

Image-Correlation Data Association with Global Uncertainty Techniques

Stephen C. Stubberud

Department of Advanced Technology
Oakridge Technology
San Diego, CA, USA
scstubberud@ieee.org

Kathleen A. Kramer

Department of Engineering
University of San Diego
San Diego, CA, USA

Abstract—A data association technique for target tracking that uses image correlation is enhanced by incorporating uncertainty. The approach uses fuzzy logic to simplify the mapping of the uncertainty to a usable construct to adjust the image generation based on the uncertainty of the measurements. The application of the uncertainty mapping for two methods is developed. The first technique varies the size of the image based on uncertainty. The second modifies the phase variation range that is used to generate the elements in the tile. The techniques are compared to the baseline image correlation technique in a baseline target-tracking example.

Keywords- Data fusion; data association; image correlation; fuzzy logic application; uncertainty.

I. INTRODUCTION

In data fusion applications, one of the most important steps in the process is the data association step [1, 2]. No matter the estimation algorithm or application, a technique to determine which measurements or observations are related to existing fusion estimates or each other is necessary. In target tracking, the standard method for data association is the chi-squared metric. This measure, based on the Mahalanobis distance, is a weighted measure that is used to compare two Gaussian random variables and is usually applied to kinematic distances. It is not easily applied to non-kinematic information, non-Gaussian distributions, or different data formats, e.g., classification and kinematics.

Another approach to data association was developed using image correlation [3]. In that effort, kinematic and classification over time was mapped to an image representation. Using this approach, a representation of the target track attributes over time, referred to as a tile, is generated. This windowed association technique, similar in concept of association to the ND-assignment problem [4], uses a phase-only filter (POF) image correlation score. While the technique of [3] had promise, it did not rely on the phase information that is the foundation of the POF. A better implementation using a phase-based tile was developed in [5, 6] that compared favorably when compared to the chi-squared metric. While the chi-square metric incorporates uncertainty, the phase-based tile approaches previously developed did not. In this work, two separate techniques to incorporate uncertainty into the association score are developed.

The first technique to incorporate uncertainty alters the size of the tile elements used for the image correlation based upon the uncertainty. Here, this is incorporated into the association and the effect on the resulting association of changing the size of the tile elements based on the uncertainty is observed. The second technique incorporates uncertainty by using phase variation mappings. Both techniques require the ability to map the variations based on the size of the uncertainties. A fuzzy logic process based the fuzzy data association technique of [7, 8] is employed by each of the two techniques in order to map the uncertainty. The application of the rescaling is global in that the entire tile is affected for each attribute based on all of the uncertainties in the time window. This is in contrast to techniques that change each measurement based on its uncertainty.

In Section 2, the image correlation technique using a phase-tile is presented. This is followed in Section 3 by an overview of tile generation. The development of the fuzzy logic used to map the uncertainty into the function that will vary the size of different attribute in the tile and the phase variation for each attribute is discussed in Section 4. Section 5 presents the technique to be used for tile size variation. The application of the fuzzy logic technique for the mapping of the phase variation is presented in Section 6. Section 7 provides a comparison of the techniques with two different tracking examples.

II. PHASE ONLY FILTER IMAGE CORRELATION

The 2-D image correlation problem has several approaches. The standard 2-dimensional image correlation function is defined by the 2-D convolution sequence

$$h(x, y) = \sum_{n=1}^N \sum_{m=1}^M g(m, n) f(x - n, y - m) \quad (1)$$

As with most straightforward mathematical techniques, the function is a computational bottleneck and memory intensive. The operational computations are $O(n^4)$ flops where n is the number of pixels along an edge (assuming a square image). The resulting image will have four times the pixels. A more efficient approach is to utilize the frequency domain implementation. This requires three 2-D fast Fourier transforms

(FFTs) and one pixel-by-pixel multiplication of the two transformed images. The resulting algorithm is given as

$$\begin{aligned} & \sum \sum f^*(x, y) * f(x + X, y + Y) = \\ & \sum \sum F^*(k_x, k_y) F(k_x, k_y) e^{-j(k_x X + k_y Y)} \quad (2) \\ & = \mathbf{F}^{-1} \left\{ \left| F(k_x, k_y) \right|^2 \right\} \end{aligned}$$

for autocorrelation, and

$$\begin{aligned} & \sum \sum g^*(x, y) * f(x + X, y + Y) \\ & = \sum \sum G^*(k_x, k_y) F(k_x, k_y) e^{-j(k_x X + k_y Y)} \quad (3) \\ & = \text{Re} \left\{ \mathbf{F}^{-1} \left\{ G^*(k_x, k_y) F(k_x, k_y) \right\} \right\} \end{aligned}$$

for cross-correlation.

Mathematically, the FFT was an improvement, but early implementers of image correlation used specific optical hardware, referred to as an optical correlator, to provide the calculations since large images could take significant computing power. Figure 1 shows the functional flow for such a device.

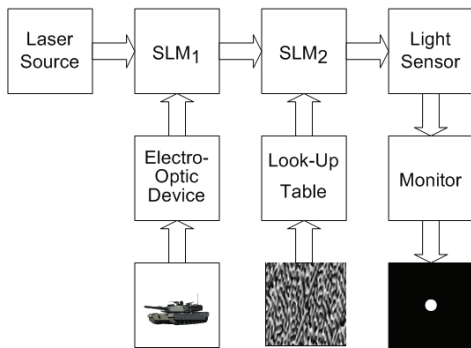


Figure 1. Function flow for optical correlator device providing image correlation

The physical limitations of the optical correlators did not exactly produce the correlation functions of Eqs. 2 and 3. Instead, the input signal became amplitude normalized such that primarily only the phase information was transmitted. The resulting equations became a phase-only filter (POF) given by

$$\begin{aligned} & \sum \sum G^*(k_x, k_y) \frac{F(k_x, k_y)}{|F(k_x, k_y)|} e^{-j(k_x X + k_y Y)} \\ & = \text{Re} \left\{ \mathbf{F}^{-1} \left\{ G^*(k_x, k_y) \frac{F(k_x, k_y)}{|F(k_x, k_y)|} \right\} \right\} \quad (4) \end{aligned}$$

As discussed in [10], the phase contained the most information of the image for comparison. As such the POF inadvertently became a powerful image correlation algorithm.

It is also worth noting that Eq. (4) is not commutative. Thus, if we change the order of the images in the cross-correlation problem, a different correlation will result.

III. TILE GENERATION

Each feature of a pattern for a given target report is comprised of an element of the tile comprised of a contiguous $n \times n$ pixel set. This set will be referred to as a sub-tile. In previous work [5], the size of the sub-tile for phase attribute matching has set to 20 pixels along each edge. This was determined to be a size that provided enough information in the frequency and phase based tiles for comparisons. These subtiles will not be fixed in size for one variant application. For the amplitude mapping approach, each attribute is assigned a region of interest or operational constraint. For example, a given pattern of data association is measured at two separate times. Position is given in terms of latitude and longitude. The third feature is the tracked altitude of the target. The fourth feature represents the measured vehicle speed. The final feature is the target heading. These values are tabulated in Table 1.

The POF correlation technique relies upon the majority of the image information being found within the phase components of the image. In contrast, the amplitude tile, first discussed in [3], uses amplitude variation to compare information. In [12], a phase representation was developed and compared well against the amplitude technique. Each attribute is mapped into a sub-tile that is defined as

$$f(x, y) = \sin(\omega x + \phi) \sin(\omega y + \phi). \quad (5)$$

TABLE I. TRACK REPORTS FOR DATA ASSOCIATION

Feature	Lat. (deg.)	Long. (deg)	Altitude (m)	Speed (m/s)	Heading (deg.)
Scan 1	32	27	2500	100	45
Scan 2	32.6	25.6	3000	100	187

The frequency is different for each attribute or feature. For each frequency used, the value of each attribute is expressed by the phase component. The region of interest for the phase of each attribute value in Eq. (5) is mapped linearly between 0° and 180° . When the pattern from Table 1 is mapped into a phase tile, the result is a two-scan image that is depicted in Figure 2. The region of interest for the features is defined between 30° and 35° for latitude, 25° and 28° for the target's longitude, an altitude range between 0 and 4000 meters, a speed between 0 and 200 m/s, and a heading between 0° and 360° .

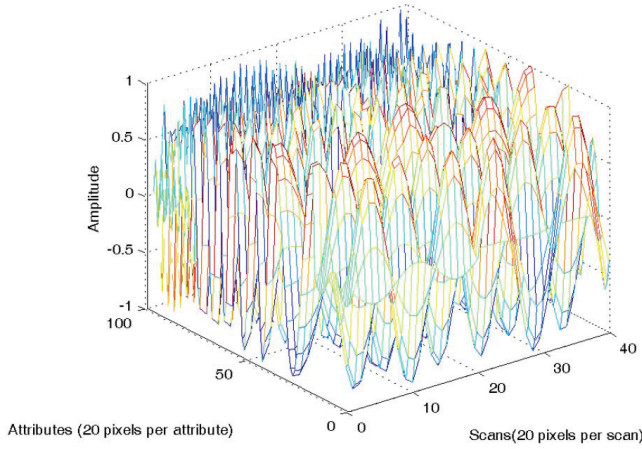


Figure 2. Two-scan image of phase tile for example data reports.

A. Normalization

The correlation function created by the POF provides a visual correlation peak that is easily understood. The function, however, does vary based on the amount of energy in the images. While this function is computationally complex, the optical correlator has it built-in via the physics and architecture. The energy variation means that comparisons require a normalization implementation. The approach used in this investigation is to compute the autocorrelation peaks of both images using the POF

$$\max \left(\max \left(POF(f(x, y), f(x, y)) \right), \max \left(POF(g(x, y), g(x, y)) \right) \right) \quad (6)$$

and to find the maximum autocorrelation of both images. This value is used to divide the values of all of the points in the cross-correlation function.

IV. FUZZY LOGIC MAPPING OF UNCERTAINTY

In [7], a fuzzy logic approach to the data association problem was developed. There, the technique used multi-layered fuzzy logic to create a score by implementing a linguistic interpretation of the chi-squared metric. It looked at closeness based on the weighted distance between the two track elements. It also looked at the overlap of the error ellipses [11]. In this approach, a similar view of the error ellipses is used. Instead of using complex mathematical distances which would be adverse to the simplicity of the image correlation technique, a basic fuzzy logic approach is developed to adjust the tile creation based on the uncertainty ellipse size and orientation.

The first variable to be mapped is that of the orientation of the error ellipses. The fuzzy memberships are defined as five potential angles of the error ellipse relative to the longitude (x-axis). As seen in Figure 3, the memberships are 0°, 45°, 90°, 135°, 180°. The alignments provide two inputs to the fuzzy decision process described in Figure 4. The first is a weighting factor that is generated using the crisp value of the antecedent functions. These weights are used in the defuzzification

process of the second defuzzification step in Figure 4. The output of the first fuzzy logic function is used to modify the the range of values that defined the consequence membership functions in the defuzzification step of the second fuzzy logic function.

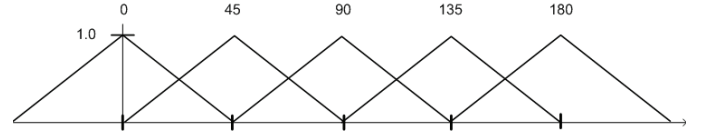


Figure 3. The antecedant triangular membership functions used to determine the alignment of the uncertainty ellipses

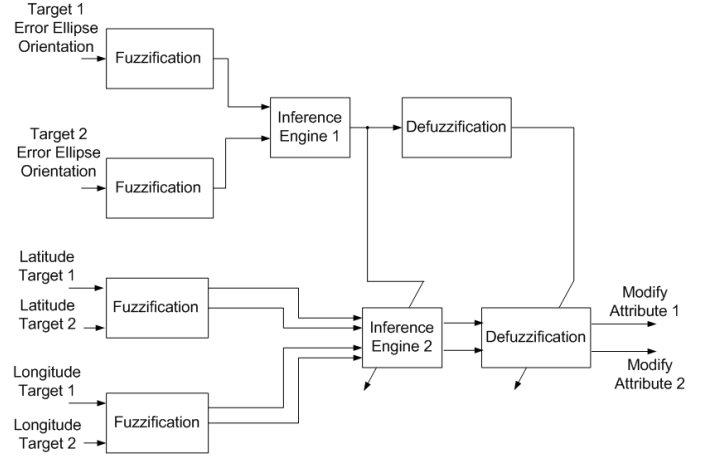


Figure 4. The fuzzy logic process to vary the tile generation used in image correlation track association process

The second input is the different rules that are activated from the inference engines in Tables 2 and 3 which relate to longitude component of the target track (or the x-axis) or the latitude component of the track (x-axis). These rules from the first stage determine vary the inputs to the inference engine the second stage (Table 4). The variations in the inputs are defined in Table 5. The input A indicates the average size of the minor or major axes of the uncertainty ellipse of Track 1 and B indicates the average of minor or major axes of Track 2. The table also indicates that multiple instantiations of the fuzzy inference engine are used in several cases.

The second process is based on the size of the axis of interest of the uncertainty ellipse. The actual uncertainty in the directions of latitude and longitude are mapped to membership functions in Figure 5. The elements of the membership functions are *small*, *medium_one*, *medium_two*, and *large*. Since the uncertainty measure is global, i.e., averaged over the entire time window, the results will affect all of the time subfiles of the entire attribute similarly. The proposed inference engine, defined in Table 4, varies depending on the alignment rule from the first step. If multiple instantiations are desired, then the output of each instantiation is weighted by the noted factor in Table 5. An NA indicates that those

rules are not used and result in a zero value for that component. The terms Maj and Min in the table refer to the major and minor axes of the uncertainty ellipses, respectively.

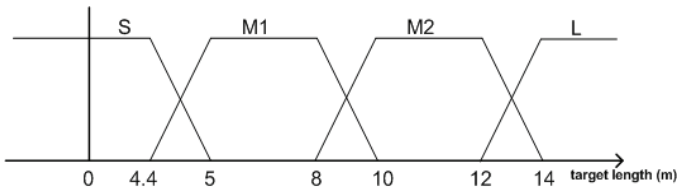


Figure 5. The antecedant triangular membership functions used to determine the size of the uncertainty ellipses axis

To simplify the development shown, the association score is generated on only the position data. The extension to include velocity would simply repeat the process on the velocity measures and uncertainties.

TABLE II. INFERENCE ENGINE MAJOR AXIS ALIGNMENT OF COVARIANCE EFFECT ON LANGITUDE (X-AXIS)

	0	45	90	135	180
	1	2	3	2	1

TABLE III. INFERENCE ENGINE MAJOR AXIS ALIGNMENT OF COVARIANCE EFFECT ON LATITUDE (Y-AXIS)

	0	45	90	135	180
	3	2	1	2	3

TABLE IV. INFERENCE ENGINE OF AVERAGED ALIGNED ERROR COVARIANCE AXIS SIZES

		B			
		Small	Medium1	Medium2	Large
A	Small	1	2	3	4
	Medium1	2	3	4	5
	Medium2	3	4	5	6
	Large	4	5	6	7

V. ATTRIBUTE PIXEL RESIZING BASED ON UNCERTAINTY

In image correlation, two images can have a noticeable difference, but, if the difference is a small percentage of the overall difference, then the images can still be highly correlated. In target tracking, if a component of the track has a large uncertainty, then the any effective difference between that component and the same component for a track or measurement to which it is being associated is reduced. The seven potential modifications will take the height of each subtitle for a given attribute from 20 pixels down to 2 pixels. This is a reduction of 3 pixels for each rule. This means the consequence membership functions becomes as seen in Figure 6.

TABLE V. ALIGNMENT EFFECTS ON THE COVARIANCE INFERENCE ENGINE AND PROCESS

Alignment		Wt.	Component							
Tgt 1	Tgt 2		A1	B1	A2	B2	A3	B3	A4	B4
1	1	1	Maj	Maj	NA	NA	NA	NA	NA	NA
1	2	0.5	Maj	Min	Maj	Min	NA	NA	NA	NA
1	3	1	Maj	Min	NA	NA	NA	NA	NA	NA
2	1	0.5	Maj	Maj	Maj	Maj	NA	NA	NA	NA
2	2	0.25	Maj	Maj	Maj	Min	Min	Maj	Min	Min
2	3	0.5	Maj	Min	Min	Min	NA	NA	NA	NA
3	1	1	Min	Maj	NA	NA	NA	NA	NA	NA
3	2	0.5	Min	Maj	Min	Min	NA	NA	NA	NA
3	3	1	Min	Min	NA	NA	NA	NA	NA	NA

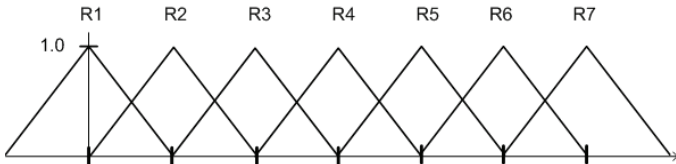


Figure 6. The consequence triangular membership functions used to determine the reduction in the attribute pixel size

The result of this approach is that large uncertainty has a lesser effect on the correlation score. This implies that the attributes (or elements of the track) with small differences relative to the uncertainty should be mapped into similar phases rather than different phases. Thus, rather than a linear mapping, the mapping should be non-linear in order to better represent attributes that effectively or near match, given the measurement uncertainty.

VI. INCORPORATING UNCERTAINTY AS A QUANTIZATION OF THE PHASE SEPARATION

The second approach to incorporating uncertainty is to vary the phase difference used in generating the subtitles. As seen in Figure 7, the linear range of values is reduced as the uncertainty becomes larger. This implies that the variation in the phase for small changes becomes less for very uncertain tracks than when the uncertainty is smaller. Thus, the association score in the former case would be greater as occurs in the chi-squared metric. The consequence function is the same as that seen in Figure 6. The defuzzified value is used to reduce the phase range.

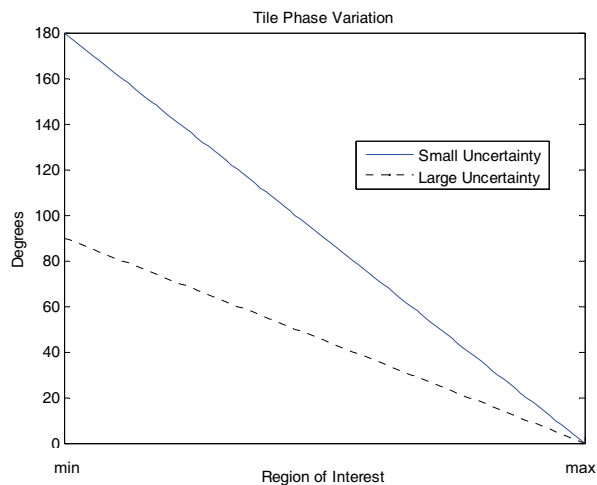


Figure 7. An example of the change in range of the phase variation based on track uncertainty

VII. EXAMPLE AND RESULTS

A scenario with two targets and three sensor systems was generated to compare the standard to the two techniques that incorporate uncertainty in a global manner. The two targets' trajectories are depicted in Figure 8 where the target on the bottom is considered Target 1 and that on top is considered Target 2. The sensor locations were chosen so that nearly parallel measurements (based on the uncertainty ellipses) were generated (Sensors 1 and 2) as the targets moved further along and nearly perpendicular target measurements were generated. These are considered extremes in target tracking and provide a good baseline.

The three sensors platforms, which are stationary throughout the scenario, are also shown in Figure 8. The three sensors are identical range-bearing sensors, i.e., a radar or active sonar, each with Kalman filter kinetic target tracking systems on them. As noted previously, the target tracks are associated with only the position data for this effort.

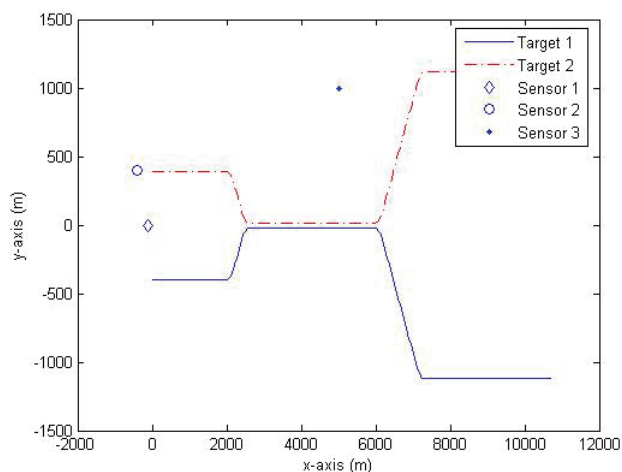


Figure 8. Example scenario with two targets and three sensors

The association scores of the track of Target 1 produced by the tracker of Sensor 1 compared to the two tracks of Sensor 2 are seen in Figures 9-11. Figure 9 depicts the association results of the original correlation technique without uncertainty. The results as in past efforts [7, 8] provide the ability to discern the two targets. In Figure 10, the uncertainty approach using the global resizing of the height of each attribute based on the average uncertainty is shown. In this case, the early portion of the track association does significantly better than without the uncertainty. At the end of the trajectory, the results are similar. This is due to the affects of the larger cross-range error of the sensor reports as the target gets further from the sensors. The cross-range error, especially for Sensor 1, is primarily in the direction of the y-axis. This is where the difference between the two targets exists in position. Figure 11 shows that the phase modification based uncertainty has a greater, and overall better, effect on the association scoring.

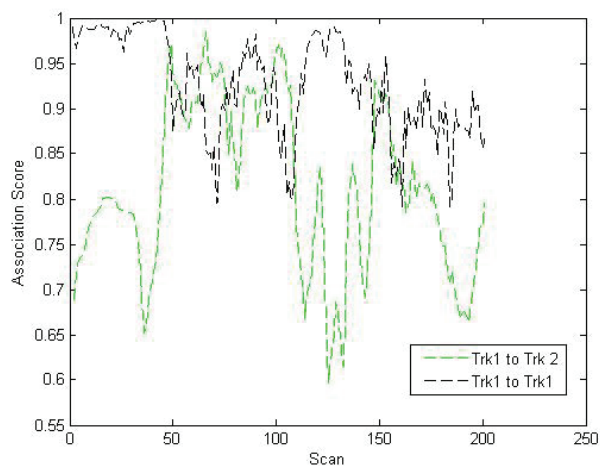


Figure 9. Association results for Sensor 1 and Sensor 2 without incorporating uncertainty

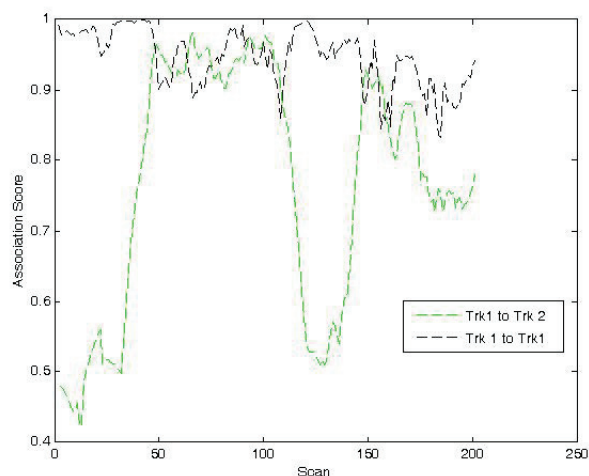


Figure 10. Association results for Sensor 1 and Sensor 2 incorporating global resizing

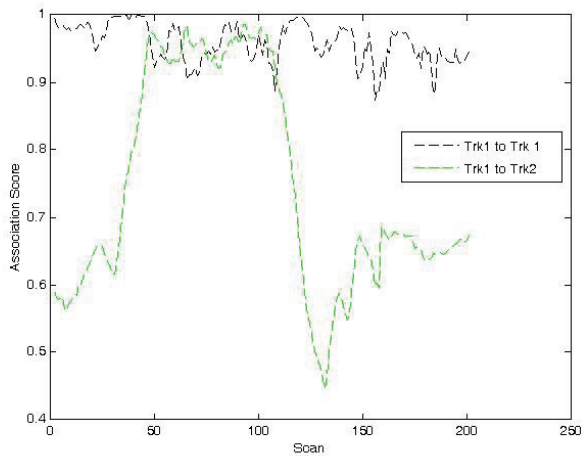


Figure 11. Association results for Sensor 1 and Sensor 2 incorporating phase modification based uncertainty

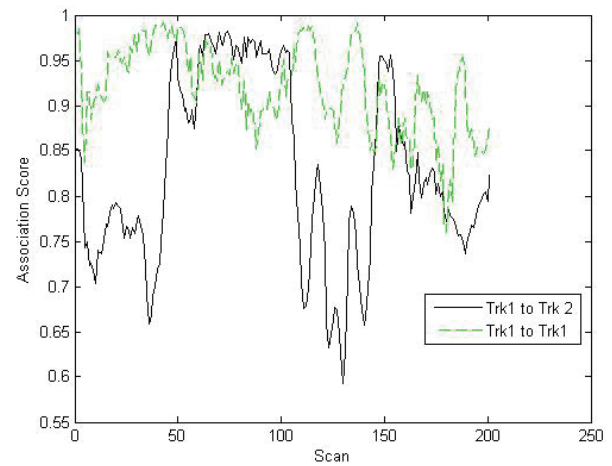


Figure 12. Association results for Sensor 1 and Sensor 3 without incorporating uncertainty

Figures 12-14 show the same comparisons as above but between Track 1 from Sensor 1 and both Tracks from Sensor 3. Similar results are obtained. The main differences that are seen are a result of the placement of the Sensor 3, which is perpendicular to Sensor 1 but closer to the end of the trajectory of the targets.

VIII. CONCLUSIONS

In this paper, two new approaches to incorporate uncertainty into the tile generation technique using fuzzy logic were introduced and demonstrated to provide significant improvement in the association scores. The use of fuzzy logic was able to provide the algorithm with less complex process to make the adjustments to the parameters used in the tile generation than if a full model of the process were developed.

Each technique was a global one in that the entire attribute component of the tile was changed based on the fuzzy system output. Future efforts are to show that by modifying only the input to the fuzzy system, the time component of each attribute can be changed with better results while allowing the fuzzy system to remain unchanged.

As this work continues, tracking system with different sensors types, e.g., bearing-only sensors, will be considered. This will demonstrate the total effectiveness of the uncertainty incorporation. Another adaptation to the techniques is to explore the incorporation of non-Gaussian uncertainties. By not limiting the association routine, it will become an effective tool with new tracking systems such as the particle filter.

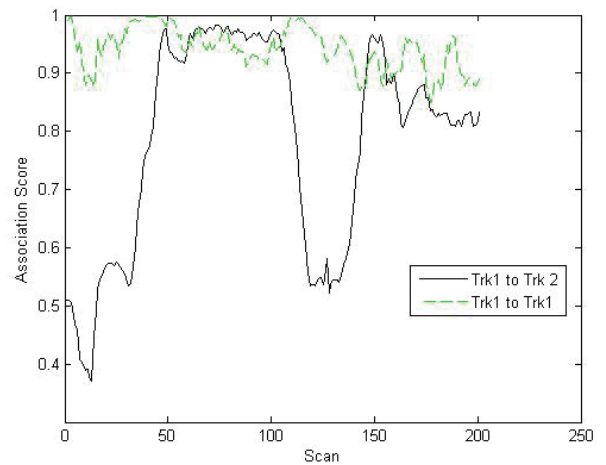


Figure 13. Association results for Sensor 1 and Sensor 3 incorporating global resizing

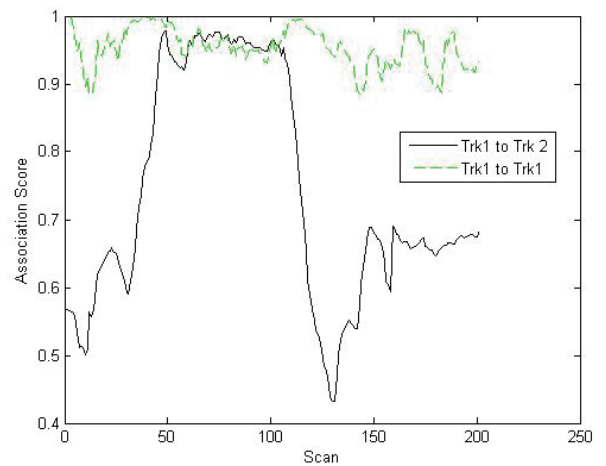


Figure 14. Association results for Sensor 1 and Sensor 3 incorporating phase modification based uncertainty

REFERENCES

- [1] D. Hall, & J. Llinas, *The Handbook of Multisensor Data Fusion*, CRC Press: Boca Raton, 2001.
- [2] S. Blackman and R. Popoli, *Design and Analysis of Modern Tracking Systems*, Artech House: Norwood, 1999.
- [3] C.J. Stanek, B. Javidi, and P.Yanni, "Performance assessment of frequency plane filters applied to track association and sensor registration," *Proc. of SPIE*, Vol. 5094, Orlando, April 2003, pp. 323-328.
- [4] A.B. Poore and A. J. Robertson III, "A new Lagrangian relaxation based algorithm for a class of multidimensional assignment problems," *Computational Optimization and Applications*, vol. 8, 1997, pp. 129-150.
- [5] S. C. Stubberud and K. A. Kramer, "Phase vs. amplitude: analysis of optically-based correlation for track association," *Proceedings of the IEEE International Conference of Systems Engineering*: Coventry, September 2009, pp. 429-433.
- [6] S. C. Stubberud and K. A. Kramer, "Effects of measurement unobservability on neural extended Kalman filter tracking," *Proc. of SPIE*, vol. 7336, Signal Processing, Sensor Fusion, and Target Recognition XVIII: Orlando, April 2010, pp. 733605.1-15.
- [7] Stubberud, S. C., Kramer, K. (2006). Data Association for Multiple Sensor Types Using Fuzzy Logic. *IEEE Transactions on Instrumentation and Measurement*, 55(6), 2292-2303.
- [8] S.C.Stubberud and K.A. Kramer, Target data association using a fuzzy-logic based approach," in *Sensor and Data Fusion, I-Tech*: Vienna, 2009, pp. 35-56.
- [9] Symmetric phase only filtering, NASA webpage: http://www.grc.nasa.gov/WWW/OptInstr/Wernet_Web/SPOF.html, 2005, accessed February 2011.
- [10] B.V.K.V. Kumar, A. Mahalanobis, and R.D. Juday, *Correlation Pattern Recognition*, Cambridge University Press: Cambridge, 2005.
- [11] S. Blackman, *Multiple-target tracking with radar applications*, Artech House: Norwood, 1986.