Disjoint Camera Track Matching by an Illumination Effects Reduction and Major Colour Spectrum Histograms Representation Algorithms

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Abstract

In this paper we present a disjoint camera track matching algorithm based on a "cumulative colour histogram transformation", the "major colour" histograms matching and the post-matching integration algorithms. In order to reduce the "effects of variable illuminations" in disjoint camera environment, a cumulative colour histogram transformation is applied to located moving object image first. Then, the Major Colour Spectrum Histogram Representation is introduced to represent a moving object in a single frame by its most frequent colours only. After that, a two-directional similarity measurement based on the MCSHR is proposed to measure the similarity of any two given moving objects in single frames. Finally, our track matching algorithm extends the single-frame matching along the objects' tracks by a post-matching integration algorithm. Experimental results presented in this paper show that the unknown illumination effects on moving objects in disjoint camera environment have been reduced significantly by using the proposed cumulative colour histogram transformation algorithm, the proposed similarity measurement algorithm can measure the similarity of the two moving objects accurately, and the post-matching integration proves able to make track matching more robust and reliable.

Keywords: Moving Object Tracking (MOT), Cumulative Colour Histogram Transformation (CCHT), Major Colour Spectrum Histogram Representation (MCSHR), Colour Distance (CD), Similarity Measurement (SM)

1 Introduction

Tracking a single object throughout a network of cameras is an important function for effective video surveillance of wide areas [1-8]. However, in most real-world camera networks it is not possible to track a moving object through a continuity of overlapping camera views. Instead, most often the object has to completely exit from the view of a certain camera before it can reappear under the view of a different one. This common scenario is often referred to as disjoint camera views, where observations of a same object are disjoint in time and space to a certain extent. In order to allow tracking in such a scenario, single-camera tracks of a same object must be matched across neighbouring cameras. The assumption in this work is that moving objects are detected and tracked in disjoint cameras, and the goal is to reduce the illumination effects in different disjoint cameras and find correspondences between such tracks. Accordingly, in this paper we present an "illumination effects reduction algorithm" for disjoint camera environment, a track matching algorithm based on the "major colour" spectrum histograms matching and the post-matching integration. First, three cumulative colour histogram transformations (R, G and B) are applied to the located moving object image to reduce the illumination effects in disjoint cameras. Then, a colour distance based on a geometric distance between two points in the RGB space is introduced to measure the similarity of any two colours. By using the colour distance and a given threshold, all pixels from a moving object MO_i in a given frame t are clustered into a limited number of colours, with each colour's frequency defined as the number of pixels with that colour. Such colours are then sorted in descending frequency order and the first k used to represent the moving object. We call this histogram the major colour spectrum histogram representation (MCSHR) representation of $MO_{i,t}$. Given two arbitrary moving objects, $MO_{i,t}$ and $MO_{j,u}$ from two different frames, t and u, a similarity criterion based on the major colour representation is used to assess their matching (single-frame matching). The single-frame matching is then extended along the two moving objects' tracks by selecting the same number of frames in each track, performing the matching between the corresponding frames of each track, and integrating the matching results along time. Finally, the time-integrated decision is compared against an assigned threshold to provide the final track matching decision. To the best of our knowledge, this is one of the first papers in the current literature to tackle the problem of track matching across disjoint camera views [6, 7]. Differently from those previous papers, our approach does not require global track matching [9] or rely on a topographic model of the camera network [10].

2 Major Colour Spectrum Histogram

2.1 Concept of Colour Distance

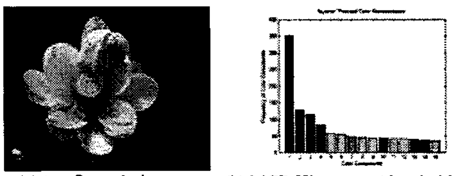
In this paper, we first introduce the concept of "colour distance" between two colour pixels in the RGB space based on a normalized geometric distance between the two pixels. Such a geometric distance is defined in equation (1).

$$d(C_1, C_2) = \frac{\|C_1 - C_2\|}{\|C_1\| + \|C_2\|} = \frac{\sqrt{(r_1-r_2)^2+(g_1-g_2)^2+(b_1-b_2)^2}}{\sqrt{r_1^2+g_1^2+b_1^2}+\sqrt{r_2^2+g_2^2+b_2^2}} \qquad (1)$$

Where C_1 and C_2 are the colour vectors. The smaller the colour distance, the more similar of is the two colours.

2.2 Moving Object Major Colour Representation

In the RGB colour space, using 1 byte to represent each colour yields a total of 16.8 million (16,777,216) different colours. It is, in general, very difficult to compare two objects based on so many possible values. By using the concept of colour distance, we can scale down the possible colours from 16.8 million to a very limited number of "Major Colours" (for example, 15 to 100) without losing much accuracy on representing a moving object. For each moving object, a given number of major colours are retained in the representation, while colours that rarely appear are discarded [11-15]. Colours within a given mutual distance threshold are dealt with as a single colour. An example of such a major colour representation is shown in Fig. 1.



(a) 'tn_flower' picture (b) MCR Histogram (threshold: 0.01)

Figure 1 The Major Colour Spectrum Histogram Representation (MCSHR) of the 'tn_flower'.

The example picture ('tn_flower') is shown in Fig. 1 (a), in which we can see that the most frequent colours are around dark green-black and yellow values. Fig. 1 (b) shows us the histogram of the major colours under the colour distance threshold of 0.01. In the histogram, we can see that there are 4 main dark green-black bins with the highest frequencies (bins 1-4). The numbers of dark green-black pixels falling in these bins are about 350, 125, 120 and 85 respectively. The yellow colours are distributed in colour spectrum bins 5, 6, 7, 8, 9, 11, 12 and 15. The numbers of pixels of yellow colours are between about 60 and 30. There are also 3 dark green-black bins spread in bins 10, 13 and 14, with the pixel numbers between 40 and 35.

3 Moving Objects Image Pre-Processing for the Disjoint Cameras

3.1 Moving Object Image Pre-Processing for Disjoint Camera

The biggest challenger in the moving objects matching in disjoint camera is the different illumination environment which has a big influence on the matching of moving objects. For example, an object in a bright illumination condition looks bright, but the same object in a dark illumination looks dark. In order to reduce the effects of variable illumination in disjoint cameras, a cumulative colour histogram transformation algorithm is proposed here, as shown in Fig. 2.

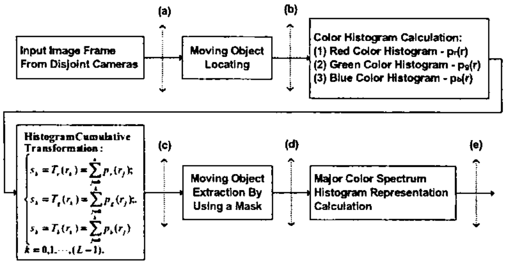


Figure 2 Moving objects image pre-processing for disjoint cameras

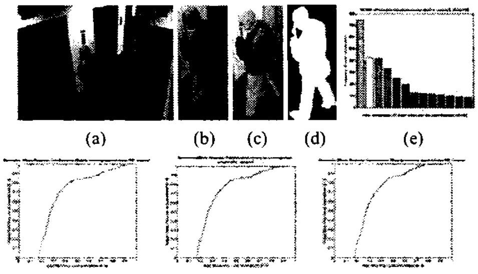
The first step in the pre-processing is moving object location and extraction. Since we focus on the "illumination effects reduction and moving objects matching in disjoint cameras" in this paper, the moving object is located and extracted manually to reduce the detection and tracking errors. In the real application, these functions will be provided automatically. The example of original input image frame and the extracted moving object are shown in Fig. 3 (a) and (b). In the second step, the colour histograms ($p_r(r)$, $p_g(r)$ and $p_b(r)$.) of moving object image are calculated for the purpose of cumulative colour histogram transformation. Then, the three cumulative colour histogram transformations (T_r, T_g and T_b) (Defined in equations (2), (3) and (4), examples shown in Fig. 3 (f), (g) and (h) respectively.) are calculated and applied to the moving object image, and the example of the colour histogram cumulative transformed moving object is shown in Fig. 3 (c).

$$s_k = T_r(r_k) = \sum_{j=0}^{k} p_r(r_j) \qquad (2)$$

$$s_k = T_g(r_k) = \sum_{j=0}^{k} p_g(r_j) \qquad (3)$$

$$s_k = T_b(r_k) = \sum_{j=0}^{k} p_b(r_j) \qquad (4)$$

By comparing the Figs. 3 (b) with (c), we can see that the contrast of moving object has been significantly improved, which is very helpful for the matching process either by computer or humans. Since the illumination conditions are normally quite different in disjoint cameras, the measures such as the above proposed "illumination effects reduction algorithm" are necessary to reduce the illumination effects. After that, the moving object is segmented by creating a moving object mask. The segmentation is also carried manually to reduce the segmentation errors. The example of the segmented moving object mask and the colour histogram cumulative transformed moving object MCSHR are shown in Fig. 3 (d) and (e) respectively.



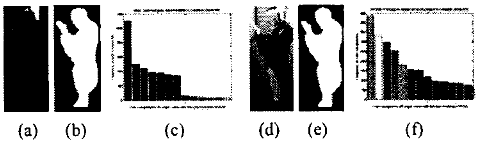
(a) (b) (c) (d) (e)

(f) (g) (h)

Figure 3 Examples of pre-processed moving object and its major colour spectrum histogram in Camera 5 frame 018 (Colour threshold: 0.01)

3.2 The Effects of Cumulative Colour Histogram Transformation on Major Colour Spectrum Histogram

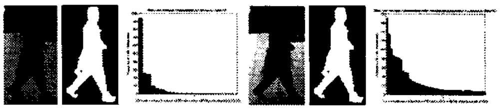
Some comparisons have been made between before and after applying moving object cumulative colour histogram transformation algorithm, and the results have been shown in Fig. 4. By comparing Fig. 4 (a) and (d), we can see that the contrast of the moving object image has been improved significantly by applying cumulative colour histogram transformation algorithm. In Fig. 4 (a), people can hardly tell the colours of the person's cloth and pans due to dark illumination, and its major colour spectrum histogram shows the dark colour accordingly. After using the "cumulative colour histogram transformation reduction algorithm", the Fig. 5 (d) shows us that clear colour difference between his cloth and pans, and much more detail colours of the persons face can easily be seen, and more detail colours of the moving object are shown in corresponding major colour spectrum histogram representation. By comparing Fig. 4 (c) and Fig. 5 (f), we can see that due to the dark illumination conditions, the major colours in the moving object are basically dark and less details can be seen, but after applying the cumulative colour histogram transformation illumination effects reduction algorithm, much more colour details can be seen in the major colour histogram representation.



(a) (b) (c) (d) (e) (f)

Figure 4 Examples of moving object and its major colour spectrum histogram in Camera 5 frame 010 (Colour threshold: 0.01) before and after using cumulative colour histogram transformation algorithm.

Another example of the effects of cumulative colour histogram transformation on moving objects in disjoint camera is shown in Fig. 5.



(a) (b) (c) (d) (e) (f)

Figure 5 Examples of moving objects and their MCSHR before and after using moving object cumulative colour histogram transformation in Camera 3a frame 011 with colour threshold: 0.01.

By comparing Fig. 5 (c) with (f), we can see that due to dark illumination condition, the number of MCSHR (24) is quite limited on original moving object, but increased significantly (50 and maximum is set to 50) and more details can be seen after applying the proposed cumulative colour histogram transformation. In conclusion, the "cumulative colour histogram transformation illumination effects reduction algorithm" can improve the major colour spectrum histogram representation of moving object significantly, more accurate and detailed colours are provided, especially in disjoint camera situation.

4 Single-Frame Matching and Post-Matching Integration Algorithm

4.1 Moving Objects Similarity Measurements

In this section, a similarity measurement based on a most similar colour searching algorithm is proposed to measure the similarity between two moving objects. This algorithm is based on the major colour spectrum histogram of the two moving objects. We assume that there are M major colours in the spectrum of moving object A, which can be represented as:

$$MCSHR(A) = \{C_{A_1}, C_{A_2}, \cdots, C_{A_i}, \cdots, C_{A_M}\} \tag{5}$$

Where $C_{A_i}, i = 1,2,\cdots,M$ is the colour vector (RGB) of major colours in object A. Object A's major colour frequencies can be represented as:

$$p(A) = \{p(A_1), p(A_2), \cdots, p(A_i), \cdots p(A_M)\} \tag{6}$$

Similarly, the major colour spectrum histogram of object B can be represented as follows:

$$MCSHR(B) = \{C_{B_1}, C_{B_2}, \cdots, C_{B_N}\} \tag{7}$$

$$p(B) = \{p(B_1), p(B_2), \cdots, p(B_N)\}. \tag{8}$$

In order to define the similarity between two moving objects, a subset of $MCSHR(B)$ in equation (7) is firstly defined as:

$$MCSHR'(B) = \{C_{B'_1}, C_{B'_2}, \cdots, C_{B'_L}\} \tag{9}$$

Where the distance between $C_{B'_j}, j = 1,2,\cdots,L$ and C_{A_k} is less than the given threshold σ.

Then, $C_{B_j|A_i}$ is defined as the most similar colour component of C_{A_i} in object B i.e. the member of subset $MCSHR(B)$ in equation (9) that satisfies equation (10).

$$d(C_{B_j|A_i}, C_{A_i}) = \underset{k=1,\cdots,L}{\arg\min}\{d(C_{B_k}, C_{A_i})\} \tag{10}$$

The portion of C_{A_i} in object A can be calculated with the following equation:

$$p_{norm}(A_i) = \frac{p(A_i)}{\sum_{i=1,2,\cdots,M} p(A_i)} \tag{11}$$

Similarly, the portion of the corresponding colour of C_{A_i} in object B can be calculated with the following equation:

$$p_{norm}^{|A_i|}(B_j) = \frac{p^{|A_i|}(B_j)}{\sum_{j=1,2,\cdots,N} p(B_j)} \tag{12}$$

Where the $p^{|A_i|}(B_j)$ is the frequency of corresponding colour of C_{A_i} in object B. Then, the similarity of colour C_{A_i} in object A with its corresponding colour C_{B_j} in object B is defined as:

$$Similarity(C_{A_i}, C_{B_j}) = \min\{\frac{p(A_i)}{\sum_{i=1,2,\cdots,M} p(A_i)}, \frac{p^{|A_i|}(B_j)}{\sum_{j=1,2,\cdots,N} p(B_j)}\} \tag{13}$$

The similarity of object A and object B based on the most similar colour search in the direction from A to B is defined as:

$$\begin{aligned} Similarity(A,B) &= \sum_{i=1}^{M} Similarity(C_{A_i}, C_{B_j}) \\ &= \sum_{i=1}^{M} \min\{\frac{p(A_i)}{\sum_{i=1,2,\cdots,M} p(A_i)}, \frac{p^{|A_i|}(B_j)}{\sum_{j=1,2,\cdots,N} p(B_j)}\} \end{aligned} \tag{14}$$

Similarly, the similarity of colour C_{B_j} in object B with its corresponding colour C_{A_i} in object A is defined as:

$$Similarity(C_{B_j}, C_{A_i}) = \min\{\frac{p(B_j)}{\sum_{j=1,2,\cdots,N} p(B_j)}, \frac{p^{|B_j|}(A_i)}{\sum_{i=1,2,\cdots,M} p(A_i)}\} \tag{15}$$

Thus, the similarity of object B and object A based on the most similar colour search in the direction from B to A is defined as:

$$\begin{aligned} Similarity(B,A) &= \sum_{j=1}^{N} Similarity(C_{B_j}, C_{A_i}) \\ &= \sum_{j=1}^{N} \min\{\frac{p(B_j)}{\sum_{j=1,2,\cdots,N} p(B_j)}, \frac{p^{|B_j|}(A_i)}{\sum_{i=1,2,\cdots,M} p(A_i)}\} \end{aligned} \tag{16}$$

In order to derive the similarity of objects A and B, the minimum and maximum of equations (14) and (16) are defined in equations (14) and (15) respectively as:

$$Similarity_{min} = \min\{Similarity(A,B), Similarity(B,A)\} \tag{17}$$

$$Similarity_{max} = \max\{Similarity(A,B), Similarity(B,A)\} \tag{18}$$

Eventually, we combine such min and max similarities into a single final value, $Similarity_{A,B}$. If $Similarity_{min}$ is less than a given discrimination threshold, $\eta_{discrim}$, the similarity of object A and object B is simply defined as:

$$Similarity_{A,B} = \min\{Similarity(A,B), Similarity(B,A)\} \tag{19}$$

The rationale is that in this case the two similarities between A and B, (14) and (16), are very asymmetric and for this reason we decide to bound them by the lowest value. Instead, if $Similarity_{min}$ is above or equal the discrimination threshold, we define:

$$Similarity_{A,B} = 1 - \frac{Similarity_{max} - Similarity_{min}}{Similarity_{max} + Similarity_{min}} \tag{20}$$

In this case, we are confident that the two visual objects are possibly a same physical one. As a further verification, we choose to check the difference between the maximum and minimum similarities in a ratio form. In equation (20) we can see that the bigger the difference between maximum and minimum similarity, the less similar are the two tracks. Eventually, matching is assessed if $Similarity_{A,B}$ is above an assigned similarity threshold.

4.2 Single-Frame Matching and Post-Matching Integration Algorithm

In the track matching algorithm, we consider the same number of frames from each track. The algorithm is shown in Fig. 6.

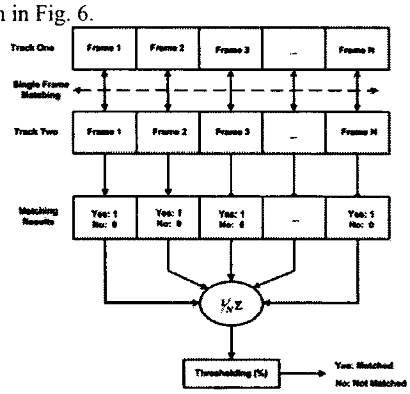


Figure 6 Single-frame matching and post-matching integration algorithms.

Fig. 6 shows us the single-frame matching as the first step of our algorithm. Moving objects from corresponding frames in Track One and Track Two are matched based on similarity of their major colour spectrum, and the matching results are given as a binary decision. The second step is the multi-frame post-integration, normalization, and thresholding. The advantages of this algorithm are:

- The single-frame matching is based on the major colour spectrum histogram and two direction similarities measurements, which makes the single-frame matching very accurate.
- The final conclusion is made based on the statistical average of single-frame matching. So, no detailed feature errors are carried forward after this stage, which makes the track matching conclusion more reliable than single frame matching.

5 Experimental Results and Analysis

In this section, we report example results from four typical tracks from three real disjoint video surveillance cameras installed in the Faculty of Information Technology building, University of Technology, Sydney, where two moving objects have been detected and tracked. In order to reduce the segmentation errors, the moving objects are segmented manually in our experiments. The segmented moving objects, major colour spectrum histograms and experimental results are shown in the following sub-sections.

5.1 The Matching of the Same Moving Person in Disjoint Cameras

The test data reported here is the same person recorded from two disjoint video surveillance cameras (reference: camera 3a, frames 001-015, and camera 5, frames 300-314.). Some of the frames are shown in Fig. 7.

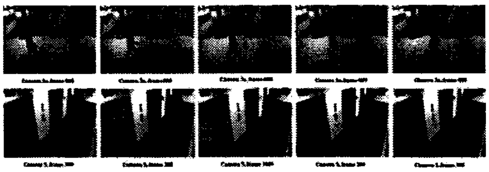


Figure 7 Moving objects from camera 3a, frames 001-009 and camera 5, frames 300-308 for single frame matching.

The single frame matching and post-matching integration results with number of major colours of 50, colour threshold of 0.01, discrimination threshold of 0.45, similarity colour threshold of 0.03 and similar matching threshold of 0.85 are shown in table 1.

Table 1 Results of Single Frame Matching and Post-Integration

Test Case	Frame No	Camera No	Similar No Tr	Match Results	Similar Tr	Match Results
1	001	3a	0.2251	0 (No)	0.9410	1 (Yes)
	300	5				
2	003	3a	0.9102	1 (Yes)	0.9611	1 (Yes)
	302	5				
3	005	3a	0.2057	0 (No)	0.9746	1 (Yes)
	304	5				
4	007	3a	0.3978	0 (No)	0.9452	1 (Yes)
	306	5				
5	009	3a	0.2332	0 (No)	0.9371	1 (Yes)
	308	5				
6	011	3a	0.1762	0 (No)	0.9913	1 (Yes)
	310	5				
7	013	3a	0.2867	0 (No)	0.9353	1 (Yes)
	312	5				
8	015	3a	0.2104	0 (No)	0.9382	1 (Yes)
	314	5				
Post-Integration	001-015	3a	N/A	12.5% (No)	N/A	100% (Yes)
	300-314	5				

The test results in table 1 show us that:

The matching (Similar A) is failed in test cases 1, 3, 4, 5, 6, 7 and 8, probably due to illumination and environment differences, but all successful after using cumulative colour histogram transformation (Similar B), and the similarities in all test cases have been improved significantly.

The post-matching integration successful rate has been improved from 12.5% to 100% after applying the proposed cumulative colour histogram transformation on moving object images.

5.2 The Matching of Two Different People from Two Disjoint Cameras

The test data reported here from two different people (reference: moving male person one, camera 4, frames 050-062; another moving male person two, camera 5, frames 010-022) in two disjoint cameras. Some frames of the moving objects in the two tracks in disjoint cameras are shown in Fig. 8.

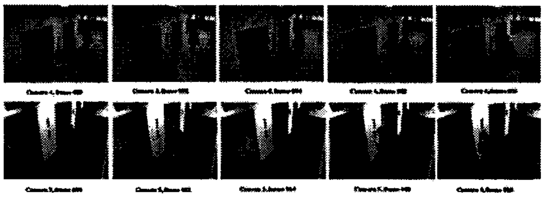


Figure 8 Moving objects from camera 4, frames 050-058 and camera 5, frames 010-018.

The results of single frame MCSHR matching and post-integration with the number of major colors of 50, color threshold of 0.01, discrimination threshold of 0.45, similarity color threshold of 0.02 and matching similarity threshold of 0.85 are shown in table 2.

Table 2 Results of Single Frame Matching and Post-Integration

Test Case	Frame No	Camera No	Similar No Tr	Matching Results	Similar Tr	Matching Results
1	050	4	0.8869	1 (Yes)	0.3880	0 (No)
	010	5				
2	052	4	0.3834	0 (No)	0.3965	0 (No)
	012	5				
3	054	4	0.3617	0 (No)	0.2584	0 (No)
	014	5				
4	056	4	0.3991	0 (No)	0.3146	0 (No)
	016	5				
5	058	4	0.3554	0 (No)	0.2937	0 (No)
	018	5				
6	060	4	0.8824	1 (Yes)	0.3667	0 (No)
	020	5				
7	062	4	0.9581	1 (Yes)	0.3751	0 (No)
	022	5				
Post-Integration	050-062	4	N/A	42.9% (Yes)	N/A	0% (No)
	010-022	5				

The test results in table 2 show us that:

1) The two different persons were wrongly matched in test cases 1, 6 and 7, probably due to poor illumination conditions, but the all successfully discriminated after using the proposed cumulative colour histogram transformations.
2) With the proposed histogram cumulative transformation algorithm, the similarities in all most all cases have been reduced a certain amount except in test case 2, in which the similarity was not reduced but still kept at low levels.
3) The integration results show us that the integrated matching rates have been reduced from 43% to 0% after using the proposed cumulative colour histogram transformation algorithm, and the discrimination ability for the above different moving objects has been increased from 57% to 100%.

The above tests show us that the unknown illumination effects on moving objects in disjoint camera environment have been reduced significantly by using the proposed cumulative colour histogram transformation. The test cases described are exemplary of the accuracy of the proposed "illumination effects reduction" and track matching algorithms. In order to make application more general, we are currently developing another compensation algorithm for global illumination variations based on colour calibration and background models, and an incremental major colour spectrum histogram (IMCSH) able to cope with small pose and appearance changes occurring along the track. In addition, the track matching procedure will be eventually integrated with other geometric features such as gait-filtered height

6 Conclusions

In this paper, a cumulative colour histogram transformation illumination effects reduction and a track matching algorithms have been proposed to reduce the illumination effects in disjoint cameras and match tracks from single objects across non-overlapping camera views. Based on our experimental results, the following conclusions can be drawn:

1) The proposed cumulative colour histogram transformation illumination effects reduction algorithm can improve the contrast of moving object significantly, and can provide more detailed colours of moving object at the same time.
2) Experimental results shown that the major colour spectrum histogram representation (MCSHR) based on the given colour distance proved able to represent moving objects accurately with a limited number of colours and their frequencies.
3) The above tests show us that the unknown illumination effects on moving objects in disjoint camera environment have been reduced significantly by using the proposed cumulative colour histogram transformation.
4) Since the post-matching integration is based on single-frame matching binary results, no detailed feature error is carried forward after this stage. Moreover, post-matching integration makes track matching more robust and reliable than single frame matching.

The proposed illumination effects reduction and track matching algorithms can significantly extend current video surveillance applications by providing them with accurate tracking matching across non-overlapping camera views which is the actual case for many real-world surveillance camera networks.

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Preface

This volume is the proceedings of the 2005 Image and Vision Computing New Zealand conference (IVCNZ), held on 28-29 November 2005 at the University of Otago in Dunedin, New Zealand.

Foreword and Welcome

On behalf of the organising committee, I would like to welcome all participants to the 2005 Image and Vision Computing New Zealand Conference and to the University of Otago in Dunedin.

The first IVCNZ conference was held in Lower Hutt in 1986. From its small beginnings as an informal gathering of New Zealand scientists, it has grown into a significant conference with many international participants. This year we received 145 submissions from all continents except Antarctica. The majority of submissions received 3 independent reviews - a mighty effort from our programme committee under quite a tight timetable. Of those 145 submissions, 30 were accepted as Oral presentations and 66 as Posters. This distinction was made based on the scores from the reviewers under the assumption that these scores were correlated with quality. Of course, no scoring system is perfect, but I believe our programme of Orals and Posters is of very good quality.

This year we have two distinguished researchers, both Fellows of the IAPR, who will present invited talks. They are Terry Caelli of NICTA, Australia, and Larry Spitz of DocRec, New Zealand.

Of course, no conference would run smoothly without significant administrative and technical support. I would like to thank our local arrangements organising committee for their help in making this conference a success and my job significantly easier. They are:
Sui-Ling Ming-Wong, Kaye Saunders, Dave Robertson and Cathy Chandra.

Finally, thanks to all the authors for submitting papers. Without you there would be no conference. Enjoy.

Brendan McCane
Dunedin, November 2005.