Correlation Filter Based Visual Tracking With Circular Shift On Local And Semi-Local Domains

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Abstract

In Parallel Consideration Of Spatial And Appearance Selective Attention Like Human Visual Perception, A Correlation Filter (CF) Can Be Estimated Based On The Association Between Object Region (Local) And Background Region (Semi-Local). In The Proposed Work, Initially, An Efficient Correlation Filter Is Estimated With The Selective Circularly Shifted (CS) Patches In The Local Domain And The Histogram Of Gradients (Hogs) In Local And Semi-Local Domains. To Effectively Remove The Boundary Effect Of The CF, The Histogram Of Gradients (Hogs) Is Extracted For Positive And Negative Samples Which In Turn Referred The Semi-Local Domains. Finally, The Linear Combination Of The Two Domain Models Is Used To Determine The Object Location. The Proposed Visual Tracking Method (OT-CS) Apparently Reduces The Distractors And Effectively Removes The Boundary Using The Combination Of Object Tracking And Circularly Shifted (OT-CS) Approach. The Proposed OT-CS Model Has Been Evaluated With Various Tracking Benchmark Datasets And Results Are Compared. The Results Show That, OT-CS Has High Contribution To Effectively Resist The Distractors With Low Computational Cost For Efficient Visual Tracking.
Keywords: Visual Tracking; Correlation Filter; Histogram Of Gradients; Object Tracking;

Nomenclature

Cf- Correlation Filter
HOG-Histogram Of Gradient
DCF- Dual Correlation Filter
SRDCF-Spatially Regularized Discriminative Correlation Filters.
MCPF-Multi Task Correlation Particle Filter
MCF-Multi-Task Correlation Filters.
MOSSE-Minimum Output Sum Of Squared Errors.
SSA-Spatial Selective Attention.
ASA –Appearance Selective Attention.
OT-Object Tracking

1.0 Introduction

Advance Research In Visual Tracking Is An Increasing Need For The Computer Vision Problems. There Have Been Lots Of Proposals For Visual Tracking Based On Different Terminologies. The Application Of Visual Tracking Widely Used In The Fields Such As Surveillance, Traffic Monitoring, Defense And Crowd Behavior Investigation. According To The Application Field, Researches Proposed Methodologies To Accompany The Visual Tracking Task. In Recent Years, Many Advances Have Been Made In Tracking Methodologies. But Still This Field Of Research Remains A Challenging Task To Track A Generic Target In Unconstrained Input Frame Sequence.

Based On The Depth Review, The Tracking Approaches Have Been Categorized Into Four Different Aspects Such As Discriminative Trackers, Generative Methods, Correlation Filter Based Trackers And Combining Trackers. Among That, Moving Object Detection Based On The Estimated

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Correlation Filter Has Flickered In Visual Tracking Approaches [1-14]. Due To The Excellent Performance Based On The Various Performance Analyses, CF Has Shown Its High Ability On The Available Benchmark Datasets [15, 16].

Henriques Et. Al., [1] Has Represented A Fast Multi-Channel Dual Correlation Filter (DCF) As An Extension Of Linear Correlation Filters. Galoogahi Et. Al. [2] Has Depicted That The Limited Boundaries In Correlation Filter Reliably Reduce The Boundary Effect. Spatially Regularized Discriminative Correlation Filters (SRDCF) [3] Has Been Estimated For Tracking Through The Spatial Location Based Spatial Regularization Component. Beyond The Conventional DCF Framework, A New Suggestion [4] Was Proposed To Continuously Learn The Convolution Filters By Interpolating The Learning Problem In A Continuous Spatial Domain. Bertinetto Et. Al. [5] Combined The Simple Trackers With Complementary Cues Of Ridge Regression Framework To Achieve The Faster Tracking.

To Focus Non-Rectangular Object Tracking, By Integrating The Filter Update And Tracking Process, DCF Tracking Has Been Introduced [6]. To Afford The Finite Results In Primitive And Dual Domain, The Optimization Problem Has Been Reformulated [7] With Multi-Dimensional. To Discriminate And Model The Forefront And Locale Discrepancies On Object With Respect To The Time A Background Aware CF Has Proposed [8] Using HOG Based Hand-Crafted Features. An Introduction Of An Unadventurous Model Training Procedures With Factorized Convolutional Variable [9] Has Reliably Tackled The Computational Complexity And Over-Fitting.

An Inherent Association Between Target Object And The Local Patches' Layout Structure Have Exploited By A Structural Sparse Tracking (SST) Algorithm [10]. A Multi-Task Correlation Particle Filter (MCPF) Has Presented [11] To Attain Forceful Visual Tracking In Terms Of Joining The Interdependencies Between Unlike Features. As An Alternative Of Simply Combine The CF And Particle Filter, A Correlation Particle Filter (CPF) [12] Has Strengthened The Both. Zang Et Al., Proposed The Method To Regularize The CF, By Exploring The Interested Region Based On Accurate Representation Of The Nonlocal Information [14] Which Yields Likelihood Map Of The Desired Object.

The Above Reviews On The State-Of-The Art Tracking Principles, One Could Realize That, The Tracking Of An Object Must Be Attentive And Selective. A Usual Canonical Correlation Filter Considers All The Non-Zero Correlation And Zero Correlation Patch In Direct Accordance With Desired Output Response Which Leads To Boundary Effect. So It Is Essential That, Tracking Methodologies Should Consider Not Only The Object Marking Bounding Box And Also It Should Consider The Background Of The Object. Also The Distractors In The Input Frames Are The Serious Issue While Estimating The Correlation Filter. It Must Be Addressed By A Precise Objective Function With High Distractor Resistance Mechanism. With This Baseline In This Work A Tracking Approach Is Proposed With A CF, Which In Turn Corresponds To The Process Concerned With Local And The Semi-Local Background Domains. This Work Specifically Contributes To Estimate A Correlation Filter Object Function With Selective Circular Shift (CS) Patches. This Distractor Resistance Approach Made An Arrangement To Overcome The Boundary Effect. The Paper Is Organized As Follows: Section 2 Presents The Tools And Techniques Used, Section 3 Give The Detailed Methodology Of The Proposed Tracking Approach And Section 4 Presents The Experimental Results Of Proposed Method And Its Performance Analysis.

2.0 Tools And Techniques

In The Context Of Visual Tracking There Have Been Many Technologies Adapted To Calculate The Response Map For Tracking. While Calculating The Response Map The Distractors May Lead To Failure, Meanwhile Distractor Resistance Approaches Lead A High Tracking Performance. The Followings Are The Techniques, Which Are Used For Distractor Resistance Approaches.

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Correlation Filter With Circular-Shift (CS)

In This Step, Spatial Selective Attention (SSA) That Is Used To Reduce The Range Of Accessible Field Of A Predictor Even As Growing Sensitivity On A Explicit Location In The Visual Field. To Solve The Minimum Output Sum Of Squared Error (MOSSE), Correlation Filter [18] As A Ridge Regression Problem With Spatial Information, Eq(1) Has Expressed.

$$C(q) = (\sum_{i=1}^{N} \sum_{j=1}^{D} \left\| y_i(j) - q^{-1} x_i[\Delta T_j] \right\|_2^2 + \lambda \|q\|_2^2) * 0.5$$

--- (1)

In Which i -Th Observation $x_i \in \Re^D$ 'S Desired Response Is $y_i \in \Re^D$, λ Denotes The Regularize Variable And $X[\Delta T] = \lfloor \Delta T_1, \Delta T_2 .... \Delta T_D \rfloor$ Is The Set With Length As D Comprise Of Circularly Shifted Image Patches. If The Object Typically At Centre Of The Image Patch Then The Objective Function Becomes

$$q = Q^{-1} \sum_{i=1}^{N} \sum_{j=1}^{D} y_i(j) x_i[\Delta T_j] \quad \text{---- (2)}$$

Where $Q = \lambda I + \sum_{i=1}^{N} \sum_{j=1}^{D} x_i(j) x_i[\Delta T]^T$.

Eq(2) Represents The Filter Which Can Compensate The Displacements In Boundary Effect. The Prominent Signature Is Hard To Estimate When Translation Plays Vital Role While Tracking. This Hard Sensitivity Is Gained Through The Introduction Of Selective Circular Shift Operator $X[\Delta T]$, These Selective Patches With Dimension D Is The Subset Of Whole Shifted Image Patches. Specifically, This Subset Leads The Distractor Resistance With High Tracking Performance.The 2D Circular-Shift In x And y Is Represented As $\Delta T = [\Delta x, \Delta y]^T$. However, The Filters Only With These Selective Circular-Shift Patches Do Not Tends To Simplify The Other Appearance Changes. So A Positive Normalization Parameter λ Is Combined. An Ensemble N > 1 Mitigates The Appearance Variation As Well As Generalization Issue. Hence, The Distractors Through Boundary Effect Relatively Reduced By The Selective Circular Shift Operator $X[\Delta T]$. Thus, The Response Map C_{t+1} Has Generated Using The Known Response Map C_t By The Eq(1).

Histogram Oriented Gradient Representation

Based On The Visual Perception Of Human, The Target And Distractors Are Categorized By The Visual Features Of The Object. This Is Termed As Appearance Selective Attention (ASA). As Like The ASA, The Model Has Evolved With Target Object Features And Distractors. These Distractors Will Be Considered As Negative Domain Samples While Learning The CF. The Distractor Resilient Matrices Are Considered From The Non-Objective Samples.

To Learn The CF Based On The Positive And Negative Or Local And Semi-Local Domain, The Multichannel HOG Feature X, $\{X_i \in \Re^{d_w^{'} d_h^{'}}\}_{i=1}^{N_x}$ Is Used. With This Feature Representation The Learning Of Cfs To Be Formulated As Spatial Domain Based Rigid Regression.

$$H(x) = \min_{w} \|Xw - y\|_2^2 + \lambda \|w\|_2^2 \quad \text{------(3)}$$

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Where $y \in \Re^{d'_w d'_h}$ Is A Target Represented As Gaussian. $X = [X_1, X_2, ..., X_{N_x}]$ With X_i Denoting The Circulant Matrix Generated By Circularly Shifting The Base Feature Vector X_i, $w = [w_1; w_2; ...; w_{N_x}]$ With w_i Denoting The Weights Of Ith Feature Channel.

At First, The Distractors From The Semi-Local Domain Are Sampled As A Set $\{X^m\}_{m=1}^{N_d}$. In Simple Terms, Manually Selected The $N_d = 4$ By Considering The Distractors Are Located In The Top, Left, Bottom And Right Of The Target Object. These Distractor Samples Are The Key Properties To Make The Tracker Comply With Robustness Tracking. Thus, The Response Map H_{t+1} Has Generated Using Known Response Map H_t By The Eq(3).

3.0 Proposed Methodology

As Stated In The Introduction, An Efficient Correlation Filter Is Estimated With Limited Boundaries Using Circular-Shift Operation In Local Domain And To Effectively Remove The Boundary Effect Of The CF, The Histogram Of Gradients (Hogs) Is Extracted For Local And Semi-Local Domains. This Proposed Model Is Named As Object Tracking Using Circular Shift (OT-CS). Figure 1 Shows The Detailed Methodology Overview.

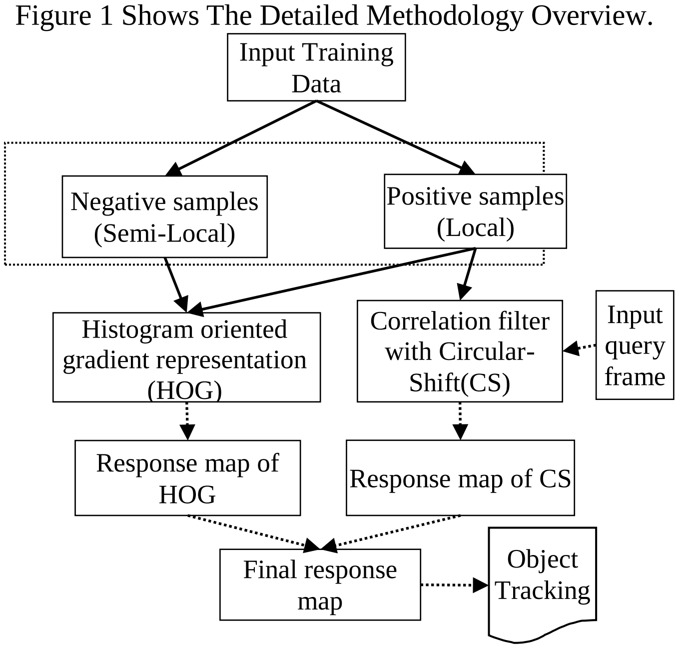

Figure 1: Flowchart Of Proposed Tracking Approach

According To The Above Stated Methodology The Proposed Framework Is Primarily Used To Detect The Desired Object Position In The Further Frames. The Known Object Location Of Present Frame Is Used For Training. It Automatically Detects The Object Location In The Next Frames. The Process Related With Both Domains Are Corresponds To Formulate A Correlation Filter (CF) Based Tracking. The Known Object Position Of The Input Frame t Is Used To Perform The Selective Circular-Shift Operation And Histogram Of Gradients (Hogs) To Effectively Remove The Distractors From Frame t. Then Both Response Maps C And H Are Linearly Combined To Estimate The Final

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Response Map R_{t+1} For The Frame T+1. The Summarized Steps Of The Proposed Tracking Algorithm OT-CS Follows

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Procedure: Object Tracking Based On CS (OT-CS)
Input: t^{th} **Observation Frame** x_t At Frame t
Procedure

1. Extract The Positive And Negative Samples X From Local And Semi-Local Domain.
2. Apply CS On Local Domain And Derive The Selective Patches $X[\Delta T]$.
3. Generate Response Map C_{t+1} By Eq(1) Using C_t.
4. Extract A Set Of HOG For The Positive And Negative Domain.
5. Learn The Optimal Weights Of Correlation Filter And Finally Obtain The Updated Weights.
6. Generate Response Map H_{t+1} By Eq(3) Using H_t.

Tracking At Frame T+1

7. Estimate The Final Response Map R_{t+1} By Linearly Combining Both C_{t+1} And H_{t+1}.

Output: Desired Response Map R_{t+1} For The Frame T+1
Training At Frame T

4.0 Experimental Results

The Proposed Algorithm Has Been Implemented Using MATLAB On A PC With An I3 3.6 Ghz CPU. The Size Of The Local Domain Is Set To $1.5X$ Target Size And $N_d = 4$. The Regularization Factor λ Is Equal To 0.025, And Learning Rate Is Fixed As 0.0625. The Number Of Padding Pixel Is Considered As 2. Moreover, The Parameters Are Same In All Experiments.

To Evaluate The Proposed Tracker OT-CS In Terms Of Accuracy, Speed And Robustness, The Experimental Analysis Has Been Carried Out On Six Benchmark Datasets Namely Dog, Biker, Blur Car, Basket Ball, Face And Bird [19]- The Subset Of These Benchmarks Has Been Taken Into Consideration For Experimental Process With Different Combination And Attributes. Accuracy Is Computed By

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Finding The Whole Difference Between The Ground Truth And The Desired Frame. Table 1 Shows The Results Of OT-CS.

Table 1 Experimental Results Of OT- CS

Dataset	**Elapsed Time(In Sec)**	**Accuracy**	**Average Error**
Dog	17.703527	**0.9467**	0.0533
Biker	18.302619	0.9200	0.0800
Blur Car	18.336841	0.6533	0.3467
Basketball	18.587526	0.2267	0.7733
Face	17.307843	**0.999**	0.001
Bird	18.742865	0.5867	0.4133

The Results Show That OT-CS Performs Outstandingly On Face, Dog And Biker Datasets. The Tracking Process Window, The Extraction Of Response Map For Local Domain And The Final Tracking Correlation Response Map Is Shown In Figure 2, Figure 3 And Figure 4 Respectively.

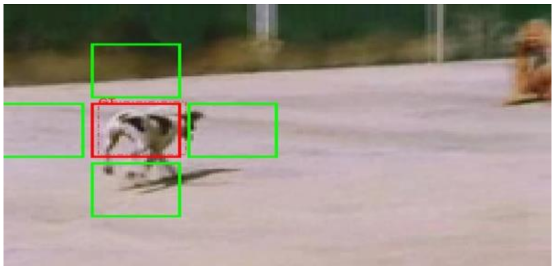

Fig 2: Tracking Process

Fig 3: Extraction Of Response Map For Local Domain

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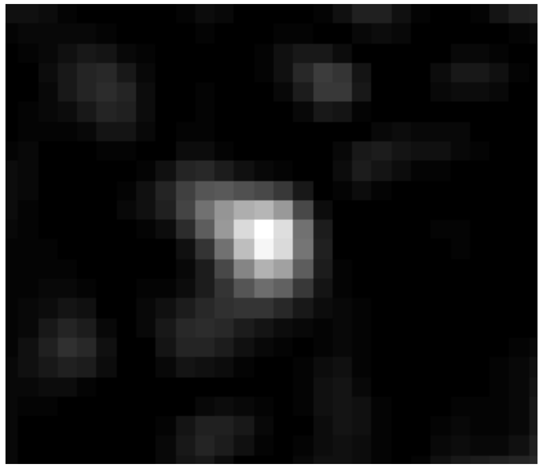

Fig 4: Final Tracking Correlation Response Map

5.0 Performance Analysis

In This Section, The Proposed OT-CS Tracker And The State-Of-The-Art Tracker OT-BMR [20] Are Compared. The Benchmark Datasets Are Used For The Evaluation Process. The Total Elapse Time For Tracking Speed, The Accuracy And Average Error Are Employed To Rank The Trackers.

Table 2: Performance Analysis Measures For The Existin OT-BMR And Proposed OT-CS Method.

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Input	Elapsed Time(In Sec)		Accuracy		Average Error	
	OT-BMR	OT-CS	OT-BMR	OT-CS	OT-BMR	OT-CS
Dog	24.146427	17.703527	0.8933	**0.9467**	0.1067	0.0533
Biker	24.099299	18.302619	0.9067	**0.9200**	0.0933	0.0800
Blur Car	23.773099	18.336841	0.5067	**0.6533**	0.4933	0.3467
Basketball	23.493379	18.587526	0.2267	**0.2267**	0.7733	0.7733
Face	22.908355	17.307843	0.999	**0.999**	0.001	0.001
Bird	24.898927	18.742865	0.4133	**0.5867**	0.5867	0.4133

Comparative Results Show That The OT-CS Outperforms Well Than Other Existing Tracker OT-BMR. Figure 5 Compares The Total Time Taken For Tracking By Existing OT-BMR And Proposed OT-CS Method. Comparative Analysis Of Accuracy With The Existing OT-BMR And Proposed OT-CS Method Is Shown In Figure 6. The Graphical Comparative Analysis Of Accuracy And Average Error Among The Existing OT-BMR And Proposed OT-CS Method Is Shown In Figure 6 And Figure 7 Respectively.

The OT-BMR Penetrates The Local Domain Features Into Correlation Filter Estimation Process As A Whole, Where As OT-CS Precisely Eliminated The Distractors Using An Elegant Selective Shifted Patches. As A Consequence, The Boundary Effect Has Resisted And Tracking Accuracy Has Also Been Improved.

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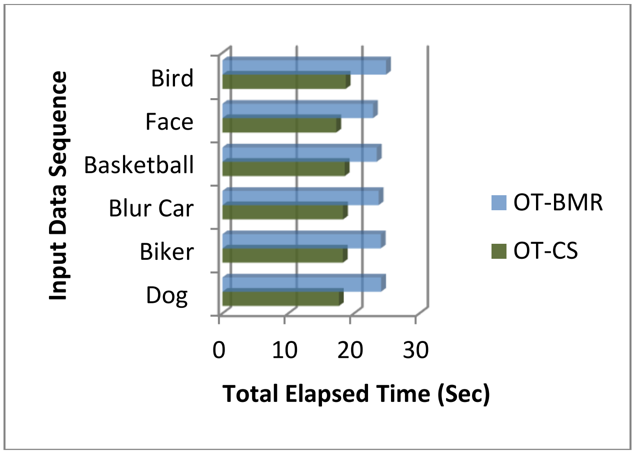

Fig 5: Analysis Of Total Time Taken For Tracking Among The Existing OT-BMR And Proposed OT-CS Method

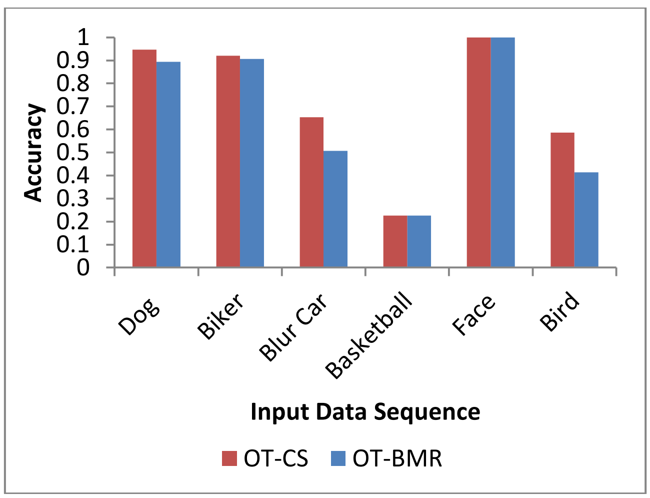

Fig 6: Analysis Of Accuracy Among The Existing OT-BMR And Proposed OT-CS Method.

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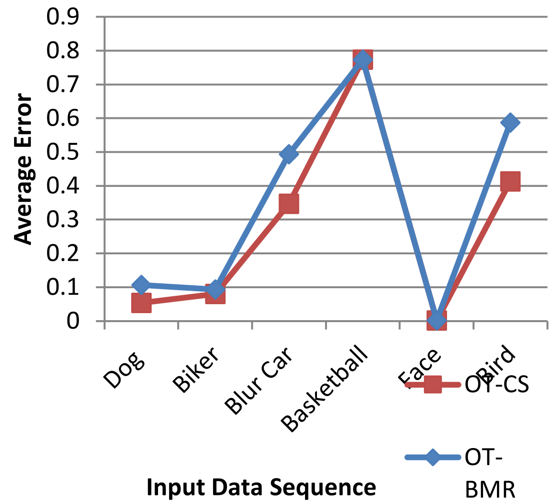

Fig 7: Analysis Of Average Error Among The Existing OT-BMR And Proposed OT-CS Method.

6.0 Conclusion

Visual Tracking Is The Widely Emerging Research In Computer Vision Applications. There Have Been The Plenty Of Methodologies Derived In The Field Of Research To Attain The Excellence In Terms Of Performance. In This Proposed Work (OT-CS), As Like Human Visual Perception, The ASA Mechanism Is Considered As Key Aspect To Learn The Cfs. The Proposed OT-CS Has Learned The Global Topological Structure Of The Object Invariant To The Different Transformations. The Distractor-Resilient Also Played The Key Role To Make Tracker Be Aware From The Distractors. The Experiments Have Been Extensively Conducted On Various Benchmark Datasets. And The Results Analysis Showed That The Proposed OT-CS Tracker Achieves Higher Performance With Minimum Tracking Time And Best Prediction Accuracy To Track The Targets.

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