1-1-2011

A Comparative Study of Three Image Matcing Algorithms: Sift, Surf, and Fast

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A COMPARATIVE STUDY OF THREE IMAGE MATCHING ALGORITHMS: SIFT, SURF, AND FAST

by

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A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Civil and Environmental Engineering

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UTAH STATE UNIVERSITY
Logan, Utah

2011

ABSTRACT

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A new method for assessing the performance of popular image matching algorithms is presented. Specifically, the method assesses the type of images under which each of the algorithms reviewed herein perform to its maximum or highest efficiency. The efficiency is measured in terms of the number of matches founds by the algorithm and the number of type I and type II errors encountered when the algorithm is tested against a specific pair of images. Current comparative studies asses the performance of the algorithms based on the results obtained in different criteria such as speed, sensitivity, occlusion, and others. These studies are an important resource to understand the behavior of the algorithms and their influence on the results obtained. But they do not account for the inherent characteristics of the algorithms that derive the process through which the matching features are evaluated, filtered, and finally selected. Moreover, these methods cannot be used to predict the efficiency or level of accuracy that could be reached by using one algorithm or the other depending on of the type of images. This ability to predict performance becomes handy in situations where time is a limiting factor in a project because it allows one to quickly predict which algorithm will save the most time and resources.

This study addresses the limitations of the existing comparative tools and delivers a generalized criterion to determine beforehand the level of efficiency expected from a matching algorithm given the type of images evaluated. The algorithms and the respective images used within this work are divided into two groups: Feature-Based and Texture-Based. And from this broad classification only three of the most widely used algorithms are assessed: SIFT, SURF, and FAST. The latter is the only one belonging to the feature-based category. Three types of images were evaluated in this study: planar surfaces, cluttered background, and repetitive patterns. For the purpose of matching planar and very "edgy" objects, such as a boat or a building, the feature-based algorithm (FAST) was found to perform with fewer detection errors than the texture-based algorithms. Conversely, when the images evaluated corresponded to cluttered backgrounds or considerably busy scenes, the texture-based detected a larger number of features and matches. The results of each algorithm are evaluated and presented. The number of false matches is manually determined and also presented in the final results. The conclusion and recommendations for feature works in this subject lead towards the improvement of these powerful algorithms to achieve a higher level of efficiency within the scope of its performance.

(120 pages)

DEDICATION

I dedicate this thesis to my parents, Ydalia and Ezequiel, for their unconditional love and support. Because despite distance you were always willing to pick up the phone and make me feel home again, I deeply love you both. To my older sister, Olga, for her genuine interest in my work and her continued motivation, I love you so much. To my oldest brother, Carlos, for those long emails full of advice, I thank you and love you. I also would like to thank my remaining sisters, Paola, Cristy, and Yuleisis for being part of my life and giving me so much love.

I couldn't have done any of this without your unconditional love and support.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my advisor and major professor, Dr. Robert Pack, for introducing me to the wonderful world of photogrammetry and computer vision. His guidance, support, and patient through this journey were endless. I wish to thank my committee members, Dr. James Bay and Dr. Xiaojun Qi, for their advice and continuous support. I also thank Keith Blonquist for his selfless help and for sharing his wide knowledge on this subject with me. I would also like to thank Erick Conde for his willingness to listen to my doubts and concerns and his thoughtful suggestions.

The financial support of our sponsor, Mr. Dean Cook, from the Naval Air Warfare Center, Weapons Division is gratefully acknowledged.

Last but not least, I would like to thank family and friends for believing in me and cheering me up when I needed it the most. I love you all.

Eng. Maridalia Guerrero Peña

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CHAPTER 1

INTRODUCTION

1.1 Problem Statement

Feature detection and image matching represent two important tasks in photogrammetry. Their application continues to grow in a variety of fields day by day. From simple photogrammetry tasks such as feature recognition, to the development of sophisticated 3D modeling software, there are several applications where image matching algorithms play an important role. Moreover, this has been a very active area of research in the recent decades and as indicated by the tremendous amount of work and documentation published around this. As needs change and become more demanding, researches are encouraged to develop new technologies in order to fulfill these needs.

In this tenor, is worth mentioning that many methods published with source code satisfy the everyday needs of photogrammetry and computer vision including feature detection, matching and 3D modeling. This latter task has been an ongoing research topic in computer vision and photogrammetry for many years now. Obtaining 3D models is considered in many cases the ultimate purpose of feature detection and subsequent matching. More than a decade ago, the applications associated with 3D models and object reconstruction were mainly for the purpose of visual inspection and robotics. Today, these applications now include the use of 3D models in computer graphics, virtual reality, communication and others.

But achieving highly reliable matching results from a pair of images is the task that some of the most popular matching methods are trying to accomplish. But none have been universally accepted. And it seems that the selection the adequate method to complete a matching task significantly depends on the type of image to be matched and in the variations within an image and its matching pair in one or many of the following parameters:

a) Scale: At least two elements of the set of images views have different scales
b) Occlusion: Is the concept that two objects that are spatially separated in the 3D world might interfere with each other in the projected 2D image plane. For single-view tasks, such as object recognition, occlusions are typically considered a nuisance requiring more robust algorithms (Hoiem et al., 2007)
c) Orientation: The images views are rotated with respect to each other . A maximum orientation of 30° is a typical maximum value for most of the algorithms to perform a reliable match
d) Object to be matched: Whether is a planar, textured or edgy object
e) Clutter: This refers to the conditions of the image background. It is often difficult form the algorithm to understand the boundaries of the object of interest when it has a cluttered background
f) Illumination: Changes in illumination also represent a typical problem for accurate feature matching

Current image matching algorithms may perform acceptably well in presence of some of the image conditions described above. But in general, none of the algorithms have truly accomplished total invariance to these parameters. More and more researchers in this area are trying to incorporate to the existing algorithms the necessary tools to achieve complete invariance to these fairly common matching problems. However, given that this is a relative novel research area in photogrammetry, it is sometimes difficult to combine all the necessary elements into one algorithm without increasing its computational cost.

Comparative studies have been published assessing the performance of the image matching algorithms methods in several aspects (Babbar et al., 2010) (Schenk, Krupnik, and Postolov, 2000). However, these studies only evaluate the algorithms in terms of how well will one perform to the other. This study overcomes some of the shortfalls and limitations of the current comparative studies by incorporating the analysis of the algorithms using different scenes to determine under which circumstances they will provide optimum results.

The challenge is to be able to evaluate the performance of each algorithm using objective criteria. This is needed to ensure the implementation of a proper methodology for the testing criteria. This will lead us to obtain results applicable to a number of possible situations. A must be evaluation focused on identifying characteristic images that when combined with a specific algorithm, will result in optimal matching. It is also necessary to determine whether the tested algorithms are capable to deliver a result that is adequate for 3D model generation.

1.2 Scope and Purpose

The main purpose of this research is to complement the already published comparative studies by adding a broader applicability that will allow the early identification of a method that will perform optimally for a given set of images.

It's within the scope of this research to provide an answer to the questions given in the problem statement. And also to discover, through an exhaustive and systematic testing program, the effectiveness of the results obtained with the image matching algorithms used in this study, when tested on different sets of images with a marked difference in texture, background clutter and other parameters. The results of each test will ultimately be used to compare the uniqueness and distinctiveness of each feature found and the final conclusion will serve as a reference for further research on this subject. In addition, is my intention to elaborate a comparative study that will present precise and condense information about the potential of each method to be used as the first step towards 3D modeling and object reconstruction. And finally, to clearly present all the derivate theory that will support such conclusions.

1.3 Organization

This thesis encompasses 6 chapters. Chapter 1 is the Introduction. Chapter 2 discusses the literature reviewed on the development of Image Matching Algorithms, their implementation, and their assessment. It is a comprehensive analysis of all the previous work in image matching algorithms development, implementation and assessment. Chapter 3 focuses on methodology. Here, the steps followed to perform the tests and to obtain the expected results are detailed. Also, it explains the method used to interpret the results. Chapter 4 provides the data analysis of the results. Chapter number 5 presents the research conclusions. Chapter 5 presents recommendations for further research in this area.

CHAPTER 2

LITERATURE REVIEW

This literature review encompasses in detail all the previous work reviewed during this research. To truly embrace image matching and 3D modeling it is important to understand the earlier works that preceded the chosen algorithms. Feature detection is the first step towards image matching which in turn represent the base for 3D modeling. The literature reviewed tracks the first attempts to achieve robust feature detection starting about two decades ago.

During the process of looking for documentation on 3D modeling, a lot of work was found that addresses the early feature detection and the posterior image matching. This is a good indicator of their importance to this process. Most of the early implementations developed seemed to work well under certain limited image condition. The real challenge for those authors was to achieve true invariant feature detection under any image conditions (i.e. illumination, rotation, blurring, scale, clutter, etc). The consistency of the early results appears to have been mostly controlled by the type of images used.

This literature review aims to provide with an insight on what have been done, what is currently being studied and where the future work is pointing in the field of image matching and automated 3D model reconstruction.

2.1 Literature Overview: Introduction to Corners, Edges and Texture Based Detectors

Robust feature detection, image matching and 3D models are concepts that have been around for many years now in the computer vision field. But it wasn't until the end of the last decade and the beginning of this one that the problem was really approached by numerous researchers and professionals working in this field. It is well known that achieving true invariant object recognition has been one of the most important challenges in computer vision and photogrammetry. Recently, there has been a significant progress in the use and implementation of algorithms towards the detection of invariant features in every-day more complex images (Lowe, 1999).

The first attempts towards digital image recognition were limited to the identification of corners and edges. This practice although effective had many limitations. The recognition of corners only in many cases was not enough for the elaboration of 3D models and object reconstruction. It therefore evolved to include another class of algorithm focused on matching textures. Both of these types are reviewed.

2.2 Feature-Based Matching Algorithms: Corner and Edge Detectors

The beginnings of feature detection can be tracked with the work of Harris and Stephen and the later called *Harris Corner Detector I* (Harris, 1988). This publication was aimed to introduce a novel method for the detection and extraction of feature-points or corners. Harris was successful in detecting robust features in any given image meeting basic requirements. But since it was only detecting corners, his work suffered from a lack of connectivity of feature-points which represented a major limitation for obtaining major level descriptors such as surfaces and objects (Harris, 1988). Due to this issue, the points detected with this method did not have the level of invariance required to obtain reliable image matching and 3D reconstructions. Nevertheless, this corner detector was a revolutionary invention that has since then been widely used for some specific computer vision applications.

In 1988, Harris published a new state-of-the-art work that marked a new direction in the work of feature detection. As a way to overcome the limitations of his previous work, he determined that there is a need for consistency in the corners detected. This is a factor of prime importance for 3D interpretation of images (Harris, 1988). To achieve this, he combined the isolated corners detected with the *Harris Detector* with a corresponding connection edge. This way, the corners randomly detected by the Harris Detector where assigned to a specific space and geometry that could be more robustly matched. The work of Harris was later improved and showed its value for efficient motion tracking and the creation of 3D structures from motion recovery.

By the end of the 1990's several corner and edge detectors were published and available to the general public. Some of these algorithms are worth mentioning because of the quality of their performance. The SUSAN corner detector and the WANG method are good examples of these algorithms (Smith and Brady, 1997); (Wang and Brady, 1994). Since then, these works have been improved and therefore superseded.

2.3 FAST Corner Detector

In 1997, almost a decade after the Harris Detector was published; a new corner detector algorithm called FAST was presented (Trajkovic and Hedley, 1998). In this work, the authors recognized the importance of the existing theory in feature detection for many tasks in Machine Vision but complemented this theory by adding other important criteria. With FAST, the detection of corners was prioritized over edges as they claimed that corners are one of the most intuitive types of features that show a strong two dimensional intensity change, and are therefore well distinguished from the neighboring points (Trajkovic and Hedley, 1998). Trajkovic and Hedley (1998) stated that to enable feature point matching from a detected corner, the corner detector should satisfy the following criteria:

a) Consistency, detected positions should be insensitive to the variation of noise and, more importantly, they should not move when multiple images are acquired of the same scene;
b) Accuracy, corners should be detected as close as possible to the correct positions;
c) Speed, even the best corner detector is useless if it is not fast enough.

According to a comparative study of the existing corner detectors based on the above criteria (Trajkovic and Hedley, 1998), was found that most of these detectors satisfied the first two criterions but failed in the third. Undoubtedly, the main contribution of FAST was the increment of the computational speed required in the detection of corners. This corner detector uses a corner response function (CRF) that gives a numerical value for the corner strength based on the image intensity in the local neighborhood. This CRF was computed over the image and corners which were treated as local maxima of the CRF. Along with this, a multi-grid technique is employed which was responsible for the improvement in the computational speed of the algorithm and also for the suppression of false corners being detected. The main contribution of FAST was summarized as: “A new algorithm which overcame some limitations of currently used corner detectors.” But FAST also modified the Harris detector so as to decrease the computational time of the algorithm without compromising the results (Trajkovic and Hedley, 1998).

Trajkovic and Hedley in his 1998 publication, compared The FAST algorithm with the top four corner detectors at the time: Harris, Modified Harris, SUSAN and Wang; the accuracy of FAST was found to be among the bests. When tested for consistency FAST performed very well; it fell just behind the best which was the Harris algorithm, but FAST was proved to be significantly faster than any other algorithm which is important for real time machine vision applications (Trajkovic and Hedley, 1998).

After the success of the FAST algorithm, several authors took the fundamentals of this method to either improve it or to implement it in new applications. In 2010 was presented one of the most relevant application and improvements of the FAST algorithm and succeeded in achieving very distinctive matching features (Fraser, Jazayeri, and Cronk, 2010).

In this publication was determined that the weakness of most of the corner detectors is the lack of effectiveness when detecting corner in a much clustered image background. This is because these detectors where based on the analysis of a pixel and its neighbors only, with no additional filtering processes this sometimes lead to erroneous detection. In the early publication already discussed (Trajkovic and Hedley, 1998) the authors were able to overcome this problem by using a linear inter-pixel approximation and lastly a multi-guard approach to reduce the sensitivity of the algorithm to false corners in textured regions of an image and to increase the computational speed of the algorithm.

With the advent of a whole new era for photogrammetry which brought with it the matching and 3D reconstruction processes, the earlier corner detectors became the starting to tool to achieve those new tasks. It is at this point where the work presented by Fraser, Jazayeri and Cronk, becomes one of the strongest contributions to this subject.

Fraser, in collaboration with Jazayeri and Cronk, presented a novel approach for feature matching and 3D reconstruction. They named their work “A Feature Based Matching Strategy for Automated 3D Model Reconstruction in Multi-image Close Range Photogrammetry” and, as it name implies, this work presented a feature-based matching approach to automated 3D object reconstruction. Fraser, Jazayeri and Cronk used the FAST interest operator developed by Trajkovic and Hedley in 1998, along with a Wallis filter applied to the image of interest (Wallis, 1974).

The work of Fraser, Jazayeri and Cronk (2000) brought FAST and the other corner-edge detector algorithms back to the spot light when it proved that, if combined with the right computational processes such as the Wallis filter, the early FAST principles were extremely effective to achieve 3D image matching and reconstruction. These authors describe the FAST operator as both a very fast and robust algorithm that yields good localization (positional accuracy) and high point detection reliability. This can be illustrated in Figure 1a, b, and c.

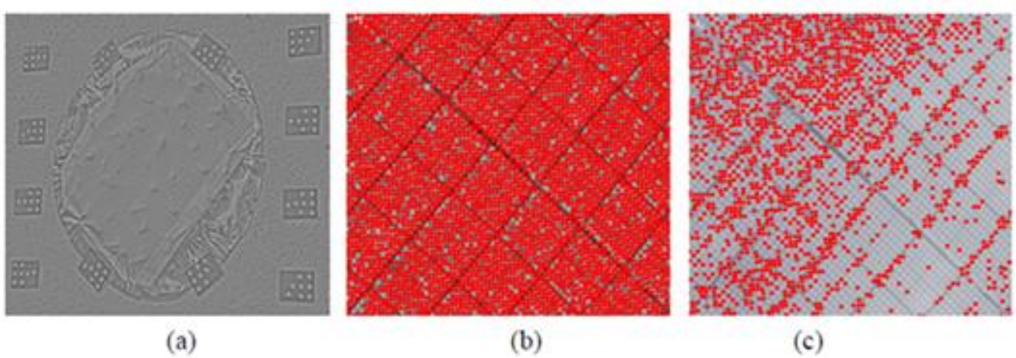

Figure 1. (a) Wallis filtered image; (b) Enlarged area showing FAST interest operator results on Wallis filtered image; (c) Enlarged area showing FAST operator results on original image.

The phenomenon of image matching through corner detectors algorithms had a strong manifestation in several more published yet seldom used algorithms. Some of them deserve to be mention for the importance of their contribution. Some of those are:

a) Least square matching algorithm. Developed by D. Rosenholm (Rosenholm, 1987)
b) Parametric correspondence and chamfer matching. Developed by Barrow in collaboration with other authors (Barrow et al., 1977)
c) Stereo image matching algorithm. This method has different approaches being the most used the layered, adaptive window and iterative approach (Kanade and Okutomi, 1994).

2.4 Textured-based Algorithms

After the development and climax of the corner detector algorithms, a new challenge was embraced: To achieve reliable image matching from textured image with cluttered backgrounds.

Before understanding this, it is important to know that feature-based algorithms have been widely used as feature point detectors because comers and edges correspond to image locations with high information content, meaning this that they can be matched between images (e.g. temporal sequence or stereo pair) reliably (Trajkovic and Hedley, 1998). But the feature-based detectors only perform accurately when the objects to be matched have a distinguishable corner or edge. In other words, feature-based detectors tend to be more suitable for matching planar surfaces and objects within a given image.

Furthermore, the feature-based algorithms do not perform as good as expected when images are subjected to variations in scale, illumination, rotation or affine transform.

To overcome these limitations, a new class of image matching algorithm was developed simultaneously. These algorithms are known as texture-based algorithms because of their capability to match features between different images despite of the presence of textured backgrounds and lack of planar and well-defined edges. One of the first attempts towards this novel approach was undertaken by David Lowe (Lowe, 1999). His method is one of the most recognized and extensively used texture-based matching algorithms.

2.5 Lowe's Approach

The ground breaking work of Lowe (Lowe, 1999) demonstrated that it was possible to detect features invariant to image scaling, translation, rotation and partially invariant to illumination. Features were efficiently detected through a staged filtering approach that identifies stable points in scale space. On top of this, image keys were created that allowed for local geometric deformations by representing blurred image gradients in multiple orientation planes and at multiple scales ensuring the detection of points within very busy backgrounds. These keys created during the filtering step, are used as input to a nearest-neighbor indexing method that identifies candidate object matches.

Final verification of each match is achieved by finding a low-residual least-squares solution for the unknown model parameters. Experimental results show that robust object recognition can be achieved in cluttered partially-occluded images with a computation time below 2 seconds.

Figure 2. Model of planar objects are in top row.

Table 1. Results presented by Lowe showing the efficiency of SIFT

Image transformation	Match %	Ori %
A. Increase contrast by 1.2	89.0	86.6
B. Decrease intensity by 0.2	88.5	85.9
C. Rotate by 20 degrees	85.4	81.0
D. Scale by 0.7	85.1	80.3
E. Stretch by 1.2	83.5	76.1
F. Stretch by 1.5	77.7	65.0
G. Add 10% pixel noise	90.3	88.4
H. All of A,B,C,D,E,G.	78.6	71.8

Table 1 presents some of the results obtained by Lowe with this work. It shows the percentage of keys found at matched locations and scales, and that also match in orientation (Lowe, 1999). As in the feature-based algorithms Lowe's approach worked really well for images of planar objects (see Figure 2), but it has a high computational cost.

2.6 Mikolajczyk and Schmid's Approach

Mikolajczyk and Schmid presented a novel approach for detecting interest points invariant to scale and affine transformations. Their approach combines the Harris detector with the Laplacian-based scale selection first presented by Lowe (Lowe, 1999). They addressed the problem of affine invariant transformation and presented a new feature detector that selects the points from a multi-scale representation (Mikolajczyk and Schmid, 2004). This methodology accomplished the detection of features invariant to affine transformations because it was suited to work with images with non-uniform scales, unlike the previous detectors. Schmid also worked in collaboration with Dorkó (Dorkó and Schmid, 2003), to present a method for constructing and selecting scale-invariant objects parts. Rather than selecting features in the entire image, this descriptor was used to extract specific objects from a set of images.

2.7 SIFT, PCA-SIFT and SURF Texture-Based Matching Algorithms

Few years after his first publication on feature detection for textured images, Lowe published an improved version of his work and presented his results with the publication of the Scale Invariant Feature Transform (SIFT) algorithm (Lowe, 2004). The concepts behind SIFT are briefly explained in the next section. Along with it, the description of other transcendental algorithms that followed SIFT is presented. These algorithms are the Principal Component Analysis-SIFT (PCA-SIFT) and the Speed-Up Robust Features (SURF).

2.8 Scale Invariant Feature Transform: SIFT

SIFT, as mentioned before, was developed by David Lowe in 2004 as a continuation of his previous work on invariant feature detection (Lowe, 1999), and it presents a method for detecting distinctive invariant features from images that can be later used to perform reliable matching between different views of an object or scene. Two key concepts are used in this definition: distinctive invariant features and reliable matching. What makes the Lowes features more suited to reliable matching than those obtained from any previous descriptor? The answer to this lies, in accordance to Lowe's explanation, in the cascade filtering approach used to detect the features that transforms image data into scale-invariant coordinates relative to local features.

This approach is what Lowe's has named SIFT, and is broken down into four major computational stages:

a) Scale-Space extrema detection
b) Keypoint localization
c) Orientation assignment
d) Keypoint descriptor

Each of these stages are execute in a descending order (that's why its referred to as a cascade approach) and on every stage a filtering process is made so that only the key points that are robust enough are allow to jump to the next stage. According to Lowe, this will reduce significantly the cost of detecting the features. However, researches who tested the SIFT algorithm stated that although SIFT seemed to be the more appealing descriptor; the 128-dimensions of the descriptor vector turn the feature detection into a relatively expensive process.

2.9 Principal Component Analysis for SIFT: PCA-SIFT

In response to this issue, new algorithms emerged as an attempt to improve SIFT and eliminate the computational costs carried with Lowe's implementations. Ke and Sukthankar were the first in presenting the "improved" version of SIFT's descriptor: PCA-SIFT (Ke and Sukthankar, 2004).

After an evaluation of the stable feature detection algorithms published by Mikolajczyk and Schmid (2004) that identified the SIFT algorithm as being the most resistant to common image transformation, Ke and Sukthankar decided to take a step further and improve the local image descriptor used by SIFT. That's how they created PCA-SIFT. This approach uses a Principal Component Analysis (PCA) to detect the local features instead of the SIFT's smoothed weighted histograms. Principal Component Analysis is a standard technique for dimensionality reduction and has been applied to a broad call of computer vision problem, including feature selection, object recognition and face recognition. While PCA suffers from a number of shortcomings, it remains popular due to its simplicity.

The PCA-SIFT achieved the ability to speed up the SIFT's matching process by an order of magnitude, but it was proved to be less distinctive than SIFT. Right after the PCA-SIFT algorithm was released developed SURF (Bay et al., 2006). SURF stands for

Speeded-Up Robust Features and it is an algorithm aimed to re-build the strengths of the leading existing feature detectors and descriptors (i.e. SIFT and PCA-SIFT).

2.10 Speeded-Up Robust Feature: SURF

The Speed-Up Robust Feature detector (SURF) was conceived to ensure high speed in three of the feature detection steps: detection, description and matching (Bay et al., 2006). Unlike PCA-SIFT, SURF speeded up the SIFT's detection process without scarifying the quality of the detected points. The reason why SURF is capable of detect images features at the same level of distinctiveness as SIFT and at the same speed as PCA-SIFT is explained by their authors as follows:

> An entire body of work is available on speeding up the matching step. All of them come at the expense of getting an approximate matching. Complementary to the current approaches we suggest the use of the Hessian matrix's trace to significantly increase the matching speed. Together with the descriptor's low dimensionality, any matching algorithm is bound to perform faster. (p.

The SIFT, PCA-SIFT and SURF algorithms are nowadays the most widely used in the computer vision community. These algorithms have proven its efficiency and robustness in the invariant feature localization (Bay et al., 2006).

2.11 Commercial Implementations

A variety of applications of the image feature matching technology can be found. One of the most popular implementations is the software developed by the Microsoft Corporation known as Photosynth. As described by their creators:

> Photosynth is really two remarkable technical achievements in one product: a viewer for downloading and navigating complex visual spaces and a "synther" for creating them in the first place. Together they make something that seems impossible quite possible: reconstructing the 3D world from flat photographs. (p.

In simple terms, Photosynth allows you to take a bunch of photos of the same scene or object and automatically stitch them all together into one big interactive 3D viewing experience. The software uses techniques from the field of computer vision to examine the selected images and find similarities between them in order to determine the point from which is image was taken. All this information is used by Photosynth to recreate a 3D scene quite similar to the real one. Other applications of the matching features include robotics, motion tracking, and human faces detection among others.

These are the type of projects that clearly succeeded in the process of implementing the concepts of one of the algorithms studied herein. The creators of Photosynth claimed to make use of the SIFT principles as the base of their work. But the manipulations and further improvements of this method remain unknown.

FAST, on the other hand, has been used in different projects by companies and individuals. A complete list of these commercial implementations can be found in the FAST web site, and it includes: Port for iphone applications, parallel tracking and mapping, Qualcomm Incorporated Technologies and others.

Another important publication on this matter is the one presented by Barazzetti, Remondino and Scaioni in 2010. In their publication "Extraction of Accurate Tie Points For Automated Pose Estimation of Close-Range Blocks" they used of SIFT and SURF algorithms to develop what they claim to be a powerful and automated methodology to extract accurate image correspondences from different kinds of close range image blocks for their successive orientation with a bundle adjustment (Bazzaretti, Remondino, and Scaioni, 2010). In other words, they developed an improved version of the Photosynth and Samantha packages explained above.

2.12 Previous Work On Matching Algorithms Comparison

During the course of this research, some people published different studies comparing Image Matching algorithms. Some of them have been very successful in comparing the most important aspects of the Image Matching algorithms.

One of the most recent comparative studies of image matching algorithms named: “Comparative Study of Image Matching Algorithms” was published in 2010 (Babbar et al., 2010). This paper based its comparative analysis on the distinction between different matching “primitives” used for these algorithms. A primitive is defined as any initial method utilized by the algorithm to detect the feature points within a given image. Two types of primitives have been discussed in this literature review so far: Feature-Based and Texture-Based. Babbar limited the scope of his study to these two primitives which he divided into two broad categories: Area Based Algorithms and Feature Base Algorithms (Babbar et al., 2010).

This study was very successful in comparing the performance of both types of algorithms in several criteria such as speed, convergence, sensitivity, occlusion and others. The conclusions of this comparative study positioned the Feature-Based algorithms as the optimal method for image matching problems in general. The reason why the Feature-Based algorithm performed the best in Babbar’s study is solely explained by the results presented in this paper where it is clear that these algorithms yielded better results in almost all the criteria tested. However, this work does not present us with the images used for the study. This leaves the door open to many uncertain facts: Were the images used were more planar than textured? If so, this may have tip the results in favor to the feature based algorithms. Or, were the set of images used to derive the results a truly representative sample of the image data-set?

Other authors have published comparative studies focusing on specific algorithms like Luo Juan and Oubong Gwun who compared the performance of SIFT, PCA-SIFT and SURF for scale changes, rotation, blur, illumination changes and affine transformation (Juan and Gwun, 2009). Again, this was a very comprehensive study where the supremacy of the texture-based algorithms was proven. The principal element of analysis for this study was the variation on the results obtained with texture-based algorithms when the set of images tested were subject to changes in the parameters above described.

Unlike Babbar's study, Juan and Gwun presented the type of images used to complete their work (Figure 3). It comes with no surprise that the types of images tested in this comparative study are highly textured.

The selection of this type of images only makes stronger the argument that not all the images can be equally evaluated with any image matching algorithm. Juan and Gwun (2009) concluded their claiming that the selection of one method over the other mainly depends on the application and recommended the future research to go towards algorithms improvements and/or application of the methods in single areas such as image retrieval and stitching to determine the suitability of each algorithm to a given set of image.

This latter comparative study concluded that SIFT was the most robust texture-based algorithm from the three evaluated, but it is too slow. SURF is significantly faster than SIFT while maintaining a good performance (comparable with SIFT). PCA-SIFT on the other hand, show its advantages in illumination and image rotation. Lastly, the study concluded with recommendations of a more in depth analysis of the images suitable to a given algorithm in dependence of the application. This is the main purpose of this research: To complement the already published comparative studies by adding a broader applicability that will allow the early identification of the method that will perform more accurately to their specific application. This is the topic that this research is expected to cover.

There are others comparative studies on image matching algorithms and an important subject that has been addressed is the surface matching comparison (Schenk, Krupnik, and Postolov, 2000).

Figure 3. Images used for the SIFT, PCA-SIFT and SURF comparative study.

CHAPTER 3

METHODOLOGY

3.1 Overview

Current methods for assessing the performance of image matching algorithms are based on comparisons of one algorithm over the other using the same image datasets. This has led to varied conclusions where sometimes one of the algorithms is presented as the best, while in other publications that same algorithms performed differently. It is believed that some algorithms are best suited to a particular type of image and that they will perform better when tested on these images. The proposed study will based its comparison on the use of different sets of images. With this, the hypothesis stating that the performance of the algorithms is dependent on the type of images evaluated will be tested.

3.2 Source Of Data: Images and Algorithms

The images to be used are representative of three different and common situations that may be present on a given set of images:

a) Cluttered Background

b) Planar Objects

c) Repetitive Patterns

The images are pictures taken from different scenes with a SONY CYBERSHOT DSC-W110 Digital Camara with a 7.2MP resolution. All the images correspond to day light scenes. The original images where resized to a lower resolution of approximately

457x630 pixels so the algorithms chosen can process them more efficiently. The images selected correspond to:

a) A window from the Technology Building at Utah State University (Repetitive Pattern)

b) A ventilation window in a brick wall (Repetitive pattern + Edge analysis)

c) The Haddock Boat (Planar Object)

d) Aggie Village Housing Building (Rotation)

Figure 4 (a) through (d) shows the image datasets used for this study.

As for the algorithms to be tested, we are using three of the most popular image matching algorithms: SIFT, SURF and FAST.

SIFT is arguably the most popular algorithm that can match under different scales, rotations and lighting, but it was significantly slow. Many implementations can be found as open source codes in the web. For this study it is used the implementation published by Rob Hess. The first version was published in 2008 but has been continuously improved until 2010. This implementation is the most recent one compilable in the Visual Studio 2008 environment and has proven to provide very good as shown in Hess's publication (Hess, 2010). Figure 5 presents some of the results obtained with Rob Hess's implementation.

(a) Repetitive pattern and clutter

(b) Edges and corners (Brick Wall)

(c) The Haddock Boat

(d) Rotation

Figure 4. The four different datasets used as the input images for the tests. (a) Repetitive pattern and clutter; (b) Edges and corners (Brick Wall); (c) The Haddock Boat (Planar Surfaces); (d) Rotation.

Figure 5. Results presented by Rob Hess with the implementation of the SIFT algorithm for object recognition. Top: SIFT features detected in two images. Bottom: SIFT featured matches between the two images.

SURF was published after SIFT and it was intended to overcome the computational cost derived from using this latter and also the amount of time consumed by the algorithm. The SURF implementation used in this study was developed by Christopher Evans in 2008 and has been continuously improved and revised up to May 2010. He also wrote the paper “Notes on the Open SURF Library” where is explained in detail the analysis of the Speeded-Up Robust Features computer vision algorithm along with a breakdown of the Open-SURF implementation. It also contains useful information on machine vision and image processing in general (Evans, 2008). This library is available in two versions: C++ and C#. The C++ version comes with the image matching component whereas the C# only has the feature detection component. Both the C++ and C# implementations are used in this study.

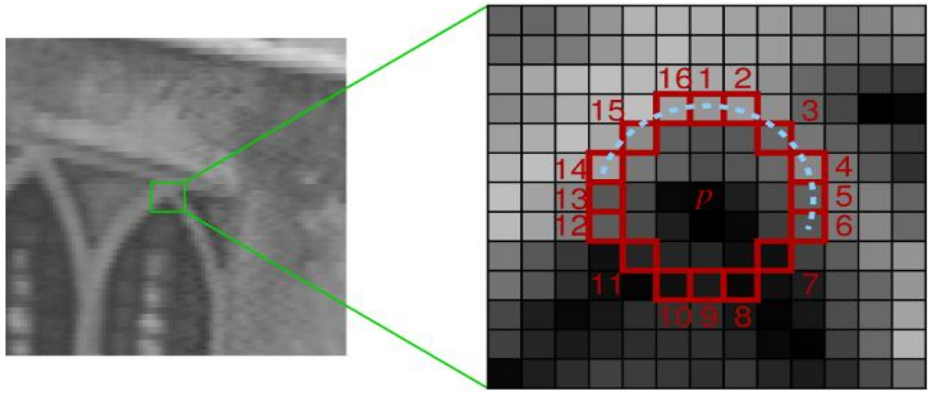

Figure 6. FAST corner detection demonstration.

FAST is the only feature-based algorithm from the three used for this study. It was first developed by Trajkovic and Hedley in 1998. The implementation used was published by Edward Rosten (Rosten and Drummond, 2009) as well. All of these implementations utilize the OpenCV library of programming functions for real time computer vision.

3.3 Experimental Process

The images shown above will be tested with each algorithm and these, in turn, will be tested in different categories having as a final and principal goal the assessment of the intrinsic algorithm characteristics that will make it differ from another. Robustness, speed, number of features and number of matches are some of the parameters that will be evaluated. Due the nature of this research we need to ensure the applicability of its results to almost any derivate circumstance in which a comparative study image vs. algorithm performance may become handy. After the data have been chosen, we will undertake an experimental process that is expected to reveal the effectiveness of the algorithms for different sets of images.

The methodology to be followed is broken down into the following steps.

3.3.1 Data selection

The images selected were described and presented in section 3.2. Each of these datasets recreates one or more of the conditions that commonly affect images and that constitute a challenge for the matching algorithms.

3.3.2 Image pairs

The images used in this study will be taken in pairs with a difference in orientation no greater than 30° from one image to its matching pair. Some of the algorithms used in this study are unable to handle images with high pixel resolution (i. e. N x M pixel size greater or equal to 1 MP). Due to this, the images taken were cropped and resized to the maximum sizes that SIFT, SURF and FAST could efficiently process. The size used for this work is 457x630 pixels. The selection of the image pairs that were tested depended on the parameters that are more significant to our purposes. It is necessary to ensure that the image pairs selected represent at least one of the parameters mentioned in section 1.1. The image pairs are shown in Figures 7-10.

3.3.3 Feature detection

After the images pairs are selected, the feature detection component of each algorithm was run over the image pairs. SIFT, SURF and FAST all are coded to perform feature detection first. The purpose of this run is to quantify the difference between the numbers of features detected by the algorithms and also the “quality” of these features.

Figure 7. Windows (First Pair).

Figure 8. Brick Wall (Second Pair).

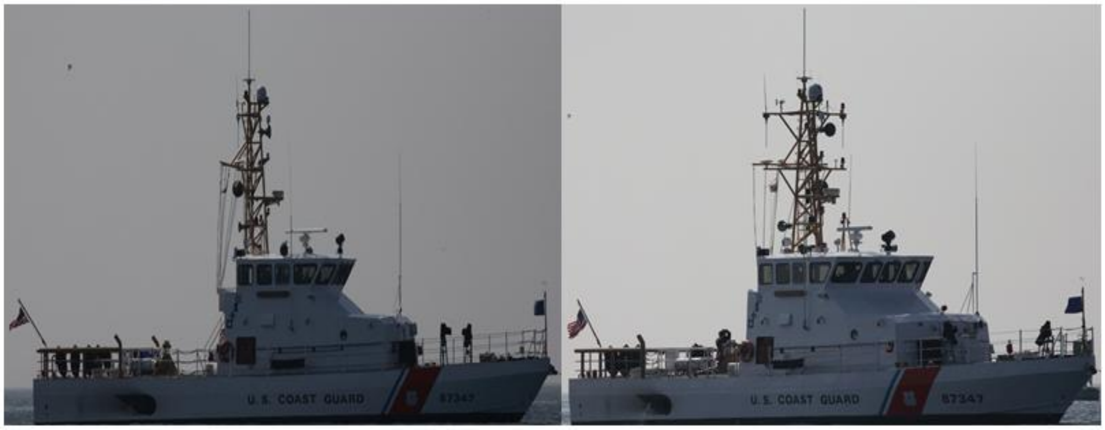

Figure 9. The Boat (Third Pair).

Figure 10. The building (Fourth Pair).

3.3.4 Manual detection of matches candidates

The amount of features detected is not a measure of a 'good' performance by itself. Better than detecting 100 features is detecting 100 *important* features in the image. Certain parts of the image contain more information than others and these are the one that will have a higher chance of finding a match candidate. A visual inspection of the features detected with SIFT, FAST and SURF was performed. A total of 20 features were manually matched at each of the image pairs (please refer to Appendix E for manual matching on image pairs). Each pair of feature detected as a match was connected to each other with a straight line, as shown in Appendix E. The process was made for each image pair and each algorithm. FAST is the only one of the three algorithms tested that does not have a matching component available as an open code. The features detected with FAST in each image pair were manually matched to determine the amount of features from image A of the pair that has a correspondent feature on Image B. Although this could be somehow 'unfair' for the other algorithms, because a manual match closely compares to a 'perfect' model, a proportionality analysis can be performed to truly assess the behavior of the three algorithms as fair as possible.

3.3.5 Automated detection of matching

After the manual matching process was completed for each algorithm, the matching component of SIFT and SURF was run. This allowed the algorithms to automatically find the matches from the feature points previously detected.

3.3.6 Evaluating the results

The results obtained from the previous steps were assessed in terms of the number of errors incurred in the detection of accurate matches by the algorithms. As a measure of the success, the errors will be classified utilizing the Type I and Type II error method. Type I error occurs when real matches are not detected by the algorithms. In this case having the algorithm found the same feature point on both images composing the pair; it does not recognize them as a match in the subsequent step. A Type II error is generated when the algorithm mismatches a feature. Typically, mismatches or false negative can be visually identified as crossing lines draw between the matches. This is further explained in Chapter 4.

Type I errors were computed by determining the number of matches that the algorithm failed to identify as matches from the ones manually detected in section 3.3.4. We want the number of type I errors to be low because a high number of type I errors reflect failures in the algorithm to accurately detect matches. For image matching algorithms we want the number of type II errors found to be low also. A high number of type II errors are a measure of inaccuracy in the algorithm because it is mismatching features within the pair.

3.3.7 Final comparison

After all the results have been collected and analyzed in depth, a comparison between the statistical values derived from the results of each method is evaluated. From this, the conclusions of this research will be shaped.

CHAPTER 4

DATA ANALYSIS

This chapter describes the step by step implementation of the methodology proposed. Some considerations and exceptions had to be made in some cases and these changes are also explained herein.

4.1 Feature Detection

4.1.1 SIFT feature detection

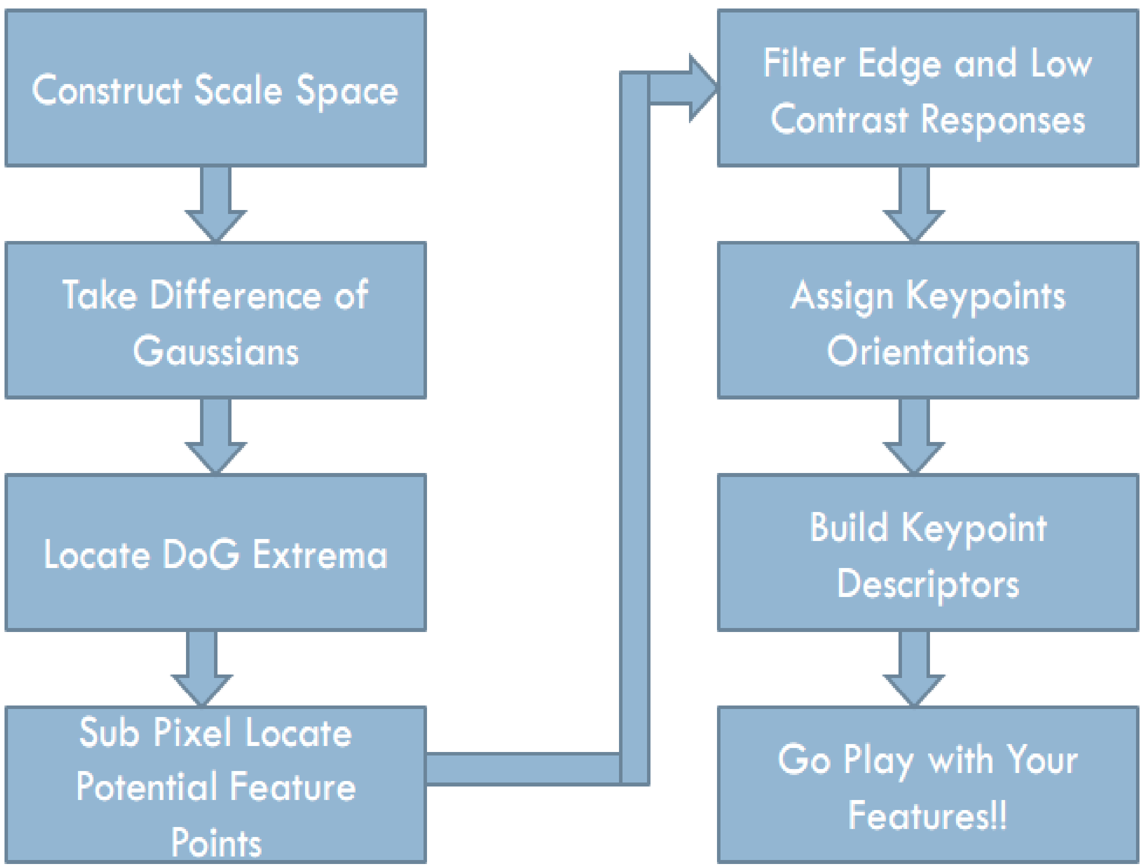

Figure 11. SIFT feature detection algorithm.

The original implementation of the SIFT algorithm feature detection can be summarized with the diagram shown in Figure 11.

Hess's implementation follows these steps in the algorithm. As explained in his paper, the SIFT Library itself comprises four main components:

a) SIFT feature detector
b) Kd-tree feature database information
c) RANSAC transform computation
d) Invariant image feature handling

To detect the interest features for the input images it is only necessary to use the first component. This SIFT Library allows you to call one of two function for detecting SIFT features both located at the "sift.h" header file that comes with the code. The first function will compute the feature detection process using the default parameters suggested by Lowe in 2004 (Lowe, 2004). The other function allows the user to select the desired parameter based on their particular interest or needs. For the tests showed here we used the default Lowe's parameters.

Images presented in Appendix A Figures 18-21 show the image pairs after the SIFT detector was run on them. The results show the features as purple arrows with different magnitudes and directions. These arrows are vectors centered at the detected point. One row is draw for each feature detected. The magnitude and direction of these rows depend on the scale and the orientations assigned to the feature they represent, respectively.

4.1.2 SURF feature detection

The OpenSURF Library is very similar to the SIFT Library when it comes to feature detection. The main difference relies on the use of an integral image from the first as the basis for this detection. The use of a very basic Hessian-matrix approximation facilitates the implementation of the integral image concept which in turn speeds up the detection. The detector is based on the Hessian matrix because of its good performance in accuracy. More precisely, the algorithm detects blob-like structures at locations where the determinant of this matrix is maximum (Bay et al., 2006).

One important reason to implement this feature extraction method is because it provides complementary information about the region of interest that cannot be obtained from edge or corner detectors. Also, the improvement on speed achieved with this implementation is a very desirable factor for many processes. The OpenSURF Library used in this study follows the steps described above (Evans, 2008).

This algorithm draws the features as ellipses of different sizes and colors. The size of each ellipse is governed by the function (`g.DrawEllipse(Pen pen, int x, int y, int width, int height`). This function takes the x and y values from the coordinates of the feature detected. The width and height parameters have the same value and are denoted by the variable S. Width and height are both factors of the feature scale. Their computation is achieved by using the following relation:

```
int S = 2 * Convert.ToInt32(2.5f * ip.scale);
```
(1)

Features are also colored blue or red on dependence of value of the Laplacian matrix. If the Laplacian value of a particular point is greater than 0, then the ellipse will be blue colored, otherwise, the resultant ellipse will be draw in red (please refer to Appendix A Figures 22-25). This is achieved by applying the following statement:

```
myPen = (ip.laplacian > 0 ? bluePen :
```
(2)

The reason why the sign of the Laplacian is important for feature detection is explained in the next lines extracted from the notes on the OpenSURF Library (Evans, 2008):

> SURF detector is based on the determinant of the Hessian matrix. In order to motivate the use of the Hessian, we consider a continuous function of two variables such that the value of the function at (x; y) is given by f(x; y). The Hessian matrix, H, is the matrix of partial derivates of the function f.

$$H(f(x,y)) = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial x \partial y} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix} \tag{3}$$

> The determinant of this matrix, known as the discriminant, is calculated by:

$$det(H) = \frac{\partial^2 f}{\partial x^2}\frac{\partial^2 f}{\partial y^2} - \left(\frac{\partial^2 f}{\partial x \partial y}\right)^2 \tag{4}$$

> The value of the discriminant is used to classify the maxima and minima of the function y the second order derivative test. Since the determinant is the product of eigenvalues of the Hessian we can classify the points based on the sign of the result. If the determinant is negative then the eigenvalues have different signs and hence the point is not a local extremum; if it is positive then either both eigenvalues are positive or both are negative and in either case the point is classified as an extremum.

4.1.3 FAST feature detection

As mentioned previously, FAST is the only feature-based algorithm from the three presented in this work. Because of this difference the process through which FAST detects feature points varies significantly from SIFT and SURF. FAST relies on a corner response function (CRF) to robustly detect corners in a given scene. It also used a multigrid algorithm to detect corners that speeds the process significantly (Trajkovic and Hedley, 1998). The three-step multigrid algorithm used to detect comers is presented below.

Step 1: In a low resolution image, compute the simple CRF at every pixel location. Classify pixels with a response higher than a define threshold T1 as ‘potential corners’.

Step 2**:** Using the full resolution image for each potential corner pixel, compute the CRF. If the response is lower than another threshold already detected, then the pixel is not a corner, and the upcoming step is not performed. If not, use a interpixel approximation and compute a new response. If the response is lower than the second threshold T2 then the pixel is not a comer.

Step 3**:** Find pixels with a locally maximal CRF and mark them as corners. This step is necessary since in the vicinity of a corner more than one point will have high CRF, and only the largest CRF is declared to be a comer point. This is called non-maximum suppression (NMS).

Features detected with FAST are drawn as blue circles on the input image. The center of the circle is located at the x and y coordinates of the feature detected. These circles have a fixed radius and thickness of 5 and 1 P respectively. Refer to Appendix A

Figures 26-29 for the FAST feature detection results on the image pairs used for this study.

4.2 Feature Matching

4.2.1 SIFT feature matching

The feature matching process is done through the match.c function in the SIFT Library. This function is explained in as follows (Hess, 2010):

> **match.c**: This application computes matches between SIFT key points detected in two images using the library's kd-tree functions and optionally computes a transform based on those matches using the library's RANSAC functions.

This is again, a matching application of the SIFT algorithm that correspond very similarly to the one described by David Lowe in his 2004 publication. The results obtained with this SIFT Library and the original are very comparable as shown in Table 2.

4.2.2 SURF feature matching

SURF uses an indexing process to accelerate the matching stage. As explained before, typically the interest feature points are derived from blob structures and this, along with the sign of the Laplacian obtained during the detection step distinguishes bright blobs on dark backgrounds from the reverse situation (Bay et al., 2006). In the matching stage, it only compare features if they have the same type of contrast, see Figure 12. Hence, this minimal information allows for faster matching, without reducing the descriptor's performance.

Table 2. A comparison of keypoint matching and computed transform accuracy between the SIFT library and David Lowe's SIFT executable

	Key points Matched	Match Percentage
SIFT Library	858 of 3705	23.20%
Lowe's executable	1087 of 4635	23.50%

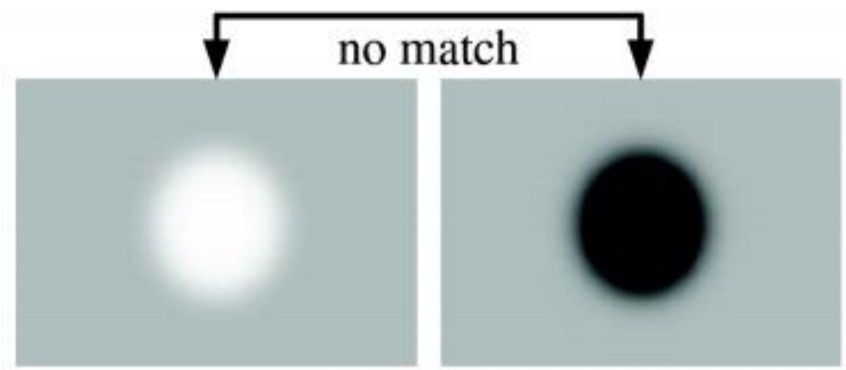

Figure 12. If the contrast between two interest points is different (dark on light background vs. light on dark background), the candidate is not considered a valuable match (Bay et al., 2006).

4.2.3 FAST feature matching

FAST matching component is not yet available as an open source code. Therefore, the automatic detection of matches could not be used in this study. However, a manual detection of the matches as explained in the third step of the experimental process. The results of this analysis and how are these results comparable with the automated matches from SIFT and SURF is detailed in Chapter 5.

CHAPTER 5

RESULTS AND CONCLUSIONS

5.1 General Overview

The experimental process followed up for this study yielded some expected results. One important consideration is that the image dataset used consists of images that represent typical cross-sections of scenes in the real world. The image size was modified to allow quick and efficient performance from the algorithms. Table 3 summarizes the number of features detected by each algorithm for a given pair of images.

5.2 Feature Detection Results

While implementing the feature detection component on the images it was found that despite the image, SIFT detects more features than FAST or SURF. The results of this feature detection process are shown in Figures 13 to 16. Given SIFT is a proven robust feature detector, it comes as no surprise the high amount of features detected in the images as shown in Appendix A Figures 18-21. The images present a high number of features detected by SIFT and these are presented by purple arrows (see section 4.1.1). However, in the majority of the images, SIFT detected features at places that did not seem to contain enough information for later matching. Corners, edges, highly contrasting, and important parts of the objects are considered good features. In the Windows pair for example (Figure 19, Appendix A), SIFT detected a lot of features in the bottom part where some tree branches are but did not detect stronger parts of the image such as corners on the window, edges, etc. Similarly, in the Brick Wall pair

(Figure 20, Appendix A) a lot of futures were detected in places that do not contain enough information. However, SIFT does detects good features in some cases. In the boat image pair for example (Figure 20, Appendix A), a lot of strong points on the boat were detected as features, but again, it can be appreciated that some features were detected in the air which doesn't seem to be a good key point candidate.

SURF follows SIFT in the amount of features detected but the difference is considerable between both for the majority of the images. SURF, although finding less, detected more "robust" features (i.e. features with enough information for later match). If we compare the results of the features detected with SURF in the Window image pair (Figure 22, Appendix A) with those detected with SIFT on the same pair, it can be seen that SURF features are mostly detected on the edges of the windows. This is a good indication of the algorithm performance, because it is selecting features that are very likely to be matched. In the brick wall pair (Figure 23, Appendix A), SURF detected features along the edges of the ventilation window. Although with some missing parts and weak features detected the overall performance of SURF detector can be described as better than SIFT for most of the images.

FAST on the other hand found very few features in all of the images tested. Given FAST is a feature-based detector, one could expect a higher amount of detections. But corner detectors usually limit themselves to detect pixels in the image with high contrast and rejected any other. Although features with more information are more desirable, this seemed to harm the performance of FAST in the quantitative aspect, but the quality of the features is undoubtedly among the best.

If we analyze the results obtain with FAST in the Window image pairs (Figure 26, Appendix A) with the results obtained with SIFT and SURF we can appreciate the robustness of FAST features over the others. These features majorly detected on the corners of the windows. FAST is not flawless, some weak features were also detected at the bottom of the Window pair. In the Brick Wall images pair (Figure 27, Appendix A), FAST did not find as much features as one would expect. This is presumably due to the lack of high contrast and poor illumination at the edges of the bricks. But FAST detected three of the four corners on the ventilation window.

Having discussed the results of the feature detection part of this study, one can say that the amount of features by itself should not be taken as measure of the effectiveness of the algorithm. It is important to determine first, how many of those features are actually robust enough to survive further filtering steps and become a positive match.

Table 3. Number of feature detected in the image dataset for the three algorithms

Features Detected				
Pair	**Image**	**SIFT**	**SURF**	**FAST**
Window Pair	A	859	770	86
	B	754	734	128
Brick Wall Pair	A	1117	507	13
	B	1106	516	6
Boat Pair	A	484	209	50
	B	604	326	294
Building Pair	A	842	606	216
	B	550	202	52

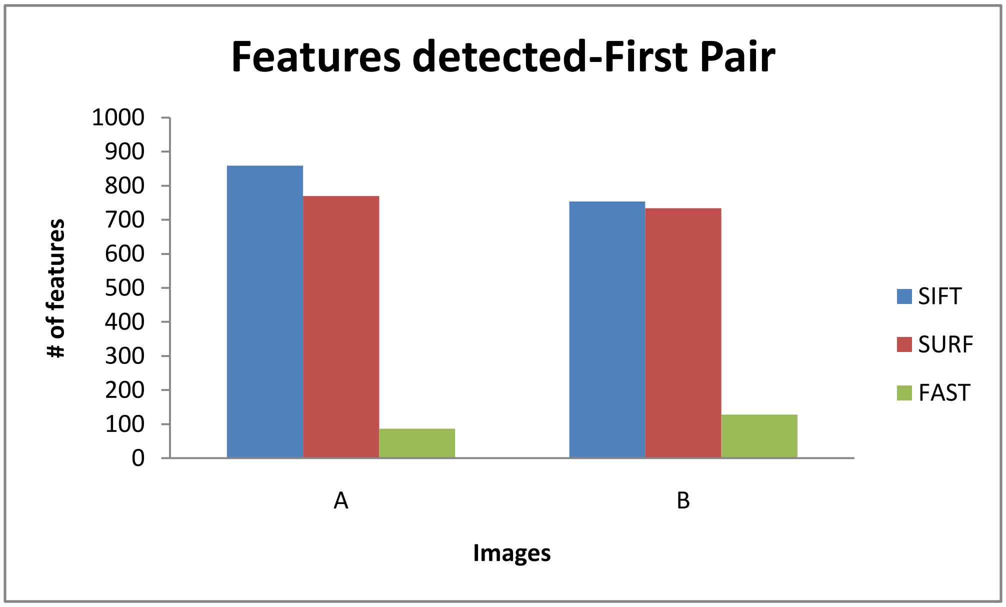

Figure 13. Features detected in the Window image pair (Images A and B).

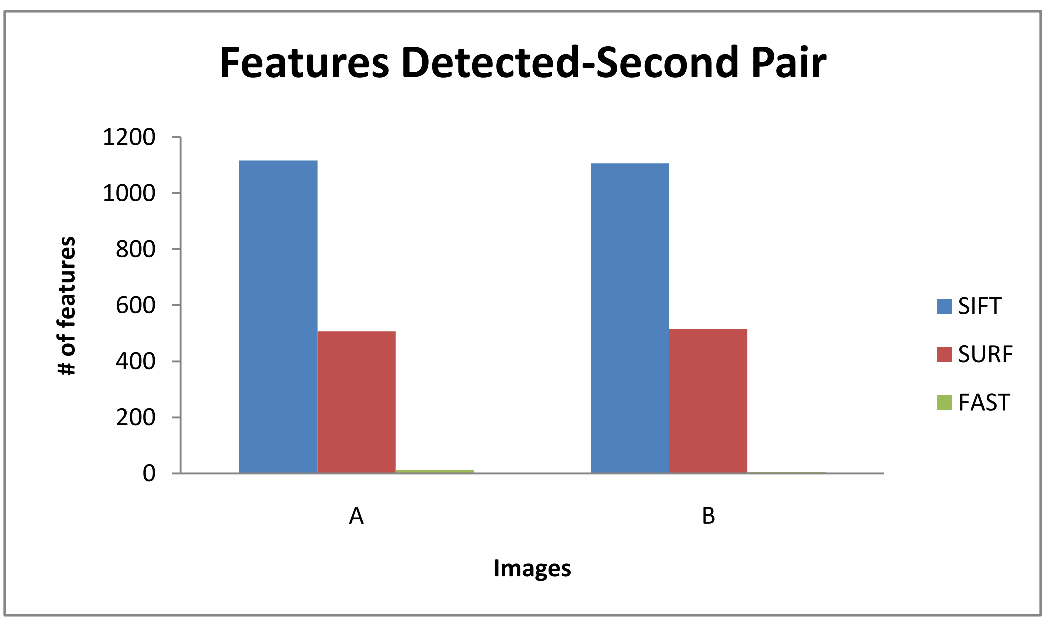

Figure 14. Features detected in the Brick Wall Image pair (Images A and B).

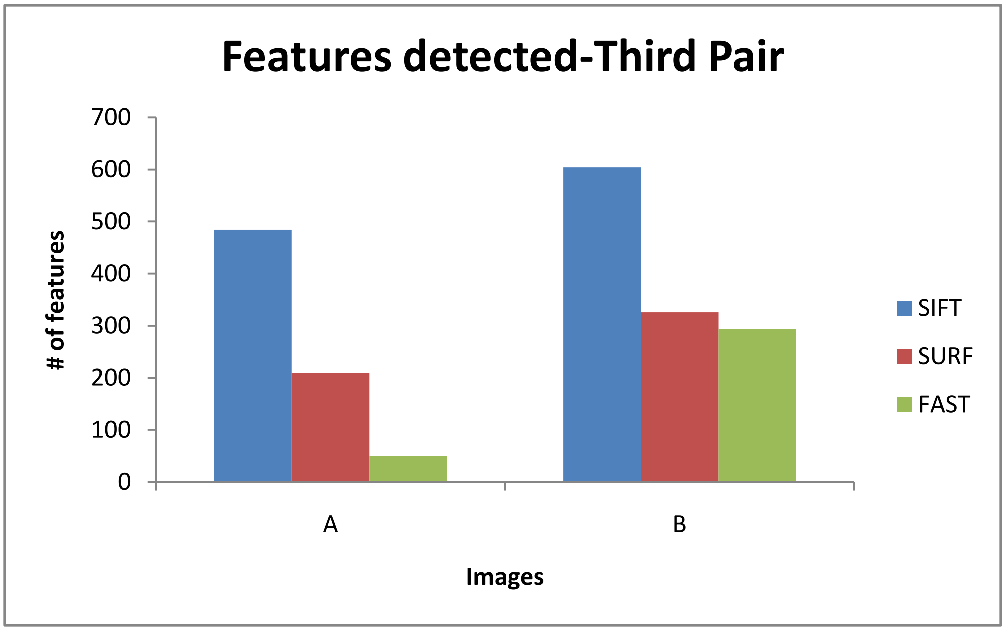

Figure 15. Features detected in the Boat Image pair (Images A and B).

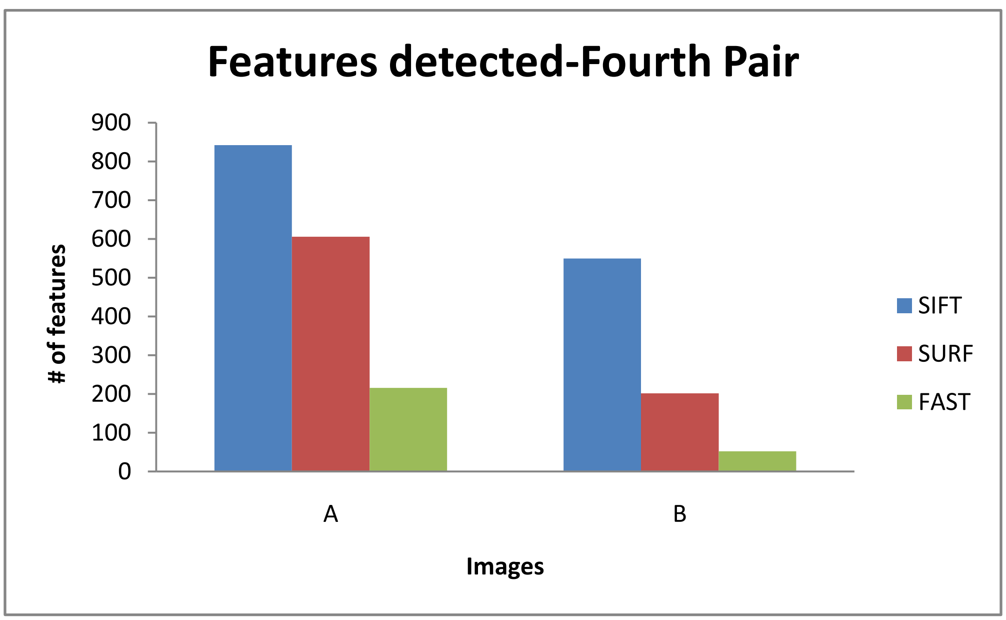

Figure 16. Features detected in the Building Image pair (Images A and B).

Let's discuss the performance of each algorithm for a given type of images. The results of this are presented in the Figure 17.

a) SIFT detected the most feature points on image No. 3. This image corresponds to the first view of the brick wall pair. This was expected because of the large amount of texture of this image (visually appreciated). On the other hand, SIFT had the lowest detection with image 5 corresponding to the first view of the Haddock Boat. This also confirm the hypothesis of SIFT performing at the highest levels when tested on textured images. This can be also checked by looking at the results for the other images.

b) SURF is also a textured based matching algorithm but it seemed to get confused in textured images with illumination changes (as is the case with the brick wall pair). Because of this, it did not have its best performance with this pair. The image with most features detected by SURF was the corresponding second one for SIFT: The window image pair (Figure 22, Appendix A). The less feature detection occurred again in the pair corresponding to the boat (Figure 24, Appendix A). This proves that SIFTS and SURF being texture-based algorithms, do not perform well when tested on planar images.

c) FAST, conversely to SIFT and SURF, detected more features in the pair comprised by the Haddock boat. Although in general the amount of features detected by FAST are significantly less than SIFT or SURF, it is appreciated that the best performance of this type of algorithms (feature-based) will be enhanced if the appropriate set of image is selected. And as explained before, FAST found the fewer amount of features in the Brick Wall image pair (Figure 27, Appendix A).

This is an unexpected result from FAST due to the large number of corners and edges within this image, but this is presumably because of the low contrast and poor illumination at the corners and edges of the brick.

The results presented in Figure 17 provide evidence that how these two types of algorithms perform is dependent on the type of image used.

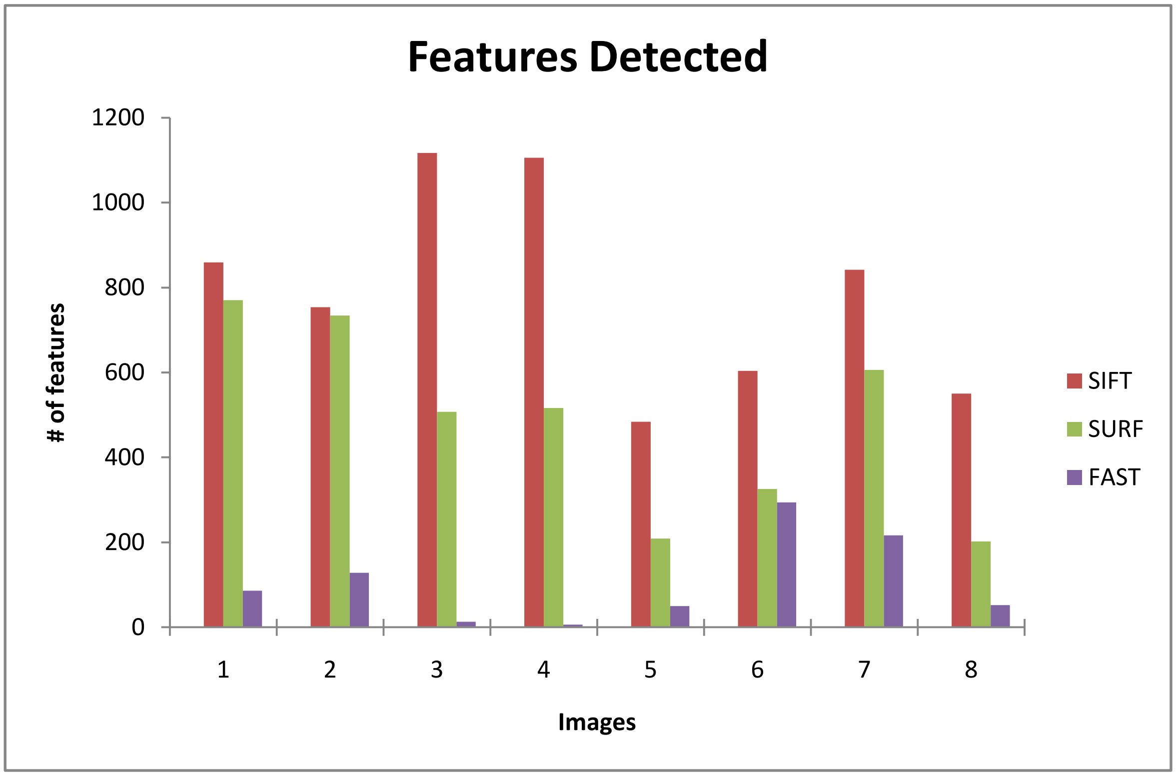

Figure 17. Overall view of the features detected on each image.

Image 1 and 2: First and second views of the Window Pair, respectively.
Image 3 and 4: First and second views of the Brick Wall Pair, respectively.
Image 5 and 6: First and second views of the Boat Pair, respectively.
Image 7 and 8: First and second views of the Building Pair, respectively.

5.3 Feature Matching Results

The reason why accurate feature detection is so important is to facilitate matching. In this step, all the features detected in one image are tested one by one against the entire database holding all the values from all the features detected in the second image to find one containing the same information. When the same information is found then a new match is originated. However, sometimes these algorithms fail to detect simple matches.

In order to measure the effectiveness and accuracy of the matching process on both SIFT and SURF algorithms, the steps described in the methodology, section 3.3, were followed. First, we created a truth dataset by taking the features detected by the algorithm and manually matching the features that that were expected the algorithm to identify as matches. For this part of the experiment we manually detected potential matches for the three algorithms. It is important to note that the source code for the matching component of FAST is not available and therefore does not take part in the detection of type II errors. The reason why the manual matches were also performed for FAST is because if this algorithm proves to be highly accurate in the detecting the same features on both images, the feature work in developing the matching component could be recommended.

The images showing the manual matches detection for SIFT, SURF and FAST can be found in Appendix D.

The following is a discussion of the algorithms matching performances for each pair of images:

SIFT: Having consistently detected more features than SURF and FAST, SIFT was, as expected, the algorithm with more matches found for each image pair. SIFT detected a maximum total of 203 matches in the Building Image pair. The lowest matches for SIFT correspond to the Windows pair with a total of 17. The pair with the Haddock boat had a total of 23 matches detected. Table 4 summarizes these results and gives a percentage of efficient based on the amount of matches found put of the totality of the features detected by SIFT.

SURF: Again, it follows SIFT in the amount of matches found among the images, proving that the amount of features detected is indeed proportional to the amount of matches. SURF had the highest matches at the Building pair, as SIFT. And the lowest detection in the third pair which is the Haddock boat pair.

FAST: As explained before, FAST does not have an automated matching component, and therefore the matches were manually identify in order to quantify the amount of features that are accurately detected in both images of the pair. The less matches were manually detected in the second image pair, the brick wall, and the most at the Building pair. However, this cannot be taken as a final conclusion because it is necessary to measure the efficiency of the matches rather than the quantity of these.

Tables 4 to 6 present the number of matches detected by each algorithm for a given pair. The effectiveness of this process is also presented. The effectiveness was calculated using the following relation:

$$\%Effectiveness = \frac{2 * \#matches}{\#features} \qquad (5)$$

By looking at the results, it can be seen that the number of matches is very low in comparison with the amount of features detected. Knowing this, we can conclude that the number of matches by itself cannot be considered good. We need to compare that amount with the amount of features detected to see how many of those features is the algorithm actually using. Automated matching from SIFT and SURF are presented in tables 4 and 5. FAST manually matching is presented in table 6. Unfortunately, the manual matching that was made for FAST cannot be compared with the automated matches from SIFT and SURF without giving an artificial conclusion. However, the results obtained with these manual matches prove that FAST detects more robust features than SIFT and SURF and that therefore are more likely to derive good matches. This is discussed in further detail in section 5.4.

Table 4. Matching performance for SIFT

	SIFT		
	Features	**# Matches**	**% Effectiveness**
Window Pair	859	17	2%
	754		
Brick Wall Pair	1177	113	10%
	1106		
Boat Pair	484	23	4%
	604		
Building Pair	842	203	29%
	550		

Table 5. Matching performance for SURF

	SURF		
	Features	**# Matches**	**% Effectiveness**
Window Pair	770	24	3%
	734		
Brick Wall Pair	507	72	14%
	516		
Boat Pair	209	10	4%
	326		
Building Pair	606	102	25%
	202		

Table 6. Matching performance for FAST

	FAST		
	Features	# Matches	% Effectiveness
Window Pair	86	17	16%
	128		
Brick Wall Pair	13	5	53%
	6		
Boat Pair	50	18	10%
	294		
Building Pair	216	26	19%
	52		

More important than the amount of matches, is the quality of these matches. Another analysis that was undertaken to determine the quality of the matches was to measure the accuracy of each of the matches. In order to do this, the matching component of the algorithms was run and allowed to automatically detect matches. Once the matches were automatically detected, the accuracy of the matches was visually analyzed and compared with the manual matches done early (see section 3.3.4). For every match from the 20 manually detected that the algorithm missed a type I error was counted. The matching process depends on the feature detection. And it is expected for a good matching algorithm to detect all the matches that can be visually or manually detected. If the algorithm does not detect those manual matches, it can be said that the matching component of such algorithm does not perform as good as it should. On the other hand, every mismatch was counted as a type II error (matching two features without being a match in the image pair). The amount of type II errors is, for this study, a more important parameter than the amount of type I. Type I errors reflect weakness in the algorithm in detecting all the matches. Type II errors reflect a failure in the algorithm for matching features without being conjugate points.

In Appendix B the automated matches detected for each pair are shown. Note that for the Brick Wall and the Building pair, SIFT and SURF again found a very large amount of matches. Therefore, it was decided to limit the number of matches detected, to make the manual error detection easier. The matches were restricted to about the same number by modifying the thresholds values. Appendix C has the matches after the parameters were modified to restrict the amount detected. The computation of type I and type II errors for SIFT and SURF is summarized in tables 7 and 8, respectively.

By comparing these two algorithms in terms of the amount of type I and type II errors it is obvious that SIFT incurred, in proportion, more errors than SURF. The large number of features detected with SIFT are not as good as those detected with SURF and because of this, it fails to match them. It is important to keep in mind that with this analysis we are not comparing the type of images that are most suitable for one algorithm or the other, because both SIFT and SURF are texture based algorithms and were proven to work similarly on the same images. With that clarified, it can be stated that in general, the features detected by these texture algorithms will not provide features good enough to accurately extract objects from a given images. Mainly because of the amount of features detected in insignificant areas of the images (this can be visually checked with the images in Appendix A).

Table 7. Type I and Type II errors detection for SIFT matches

SIFT					
Pair	**# Matches**	**Type I**	**Type II**	**Type I %**	**Type II %**
Window	17	12	14	60%	82%
Brick Wall	53	11	7	55%	13%
Boat	75	8	5	40%	7%
Building	23	4	10	20%	43%

Table 8. Type I and Type II errors detection for SURF matches

SURF					
Pair	**# Matches**	**Type I**	**Type II**	**Type I %**	**Type II %**
Window	24	5	13	25%	54%
Brick Wall	51	9	14	45%	27%
Boat	10	2	0	10%	0%
Building	74	0	9	0%	12%

5.4 Conclusions

After reviewing the results obtained in this research we can conclude the following:

a) The amount of features detected by SIFT, FAST and SURF is dependent on the type of images used.

b) SIFT and SURF, as texture-based detectors, were found to detect more features when highly texture images were used.

c) FAST on the other hand, performed more accurately where SIFT and SURF "failed". This means that FAST, being a feature-based algorithm, will perform better in when tested to images containing planar objects.

d) The amount of features is not a measure of success by itself but the "quality" of these features

e) The amount of features detected is proportional to the amount of matches.

f) SIFT was the algorithm detecting more features and matches in all the images.

g) The amount of matches detected is not a good indication of the performance of the algorithm

h) SIFT found more matches than SURF and FAST but also less effectiveness was measured

i) The effectiveness ratios were not as promising as the amount of matches. Furthermore, the amounts of type I and II errors encountered in both SIFT and SURF determined that these two algorithms need to be improved to reject some useless features and detect more robust ones.

j) FAST detected considerably less matches than SIFT but it had a better performance, proportionally.

k) Features detected by FAST, although fewer, are more robust than those detected by SIFT and SURF.

CHAPTER 6

RECOMMENDATIONS

A comparative study of three image matching algorithms has been done in this research. Results obtained proved that the hypothesis that the performance of a given algorithm depends on the type of image used is true. Visually textured and non-textured images were used to prove this. It is recommended for future research in this area to use a method to statistically evaluate the texture of the images such as the maximum entropy method. These methods use statistical analysis to measure the parts of the images with more information and develop a model of the texture of the image base on this.

It was concluded that FAST has the best overall performance above SIFT and SURF but it suffers from detecting very few features and therefore matches. It is recommended that the properties of this algorithm to be improved by creating a new implementation provided with a matching component. It is necessary to improve FAST by increasing the amount of features it can detect. But special care should be taken to preserve the robustness of the algorithm and avoid the detection of useless features.

Future research in this area should focus on testing the accuracy of the algorithms in detecting a single object within a scene. Many of the new arising needs in photogrammetry address this problem and this work could be a first step towards a more in depth study.

The results reported in this work are likely a starting point for future research on this subject where a more in-depth analysis of the algorithms structures would be done. Also, an automated assessment of the algorithms performance could follow where future researches would be able to consider a wider range of issues that need to be addressed when working with SIFT, SURF, and FAST.

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APPENDICES

Appendix A. Feature Detection Images

Figure 18. SIFT Features detected – Window Image Pair.

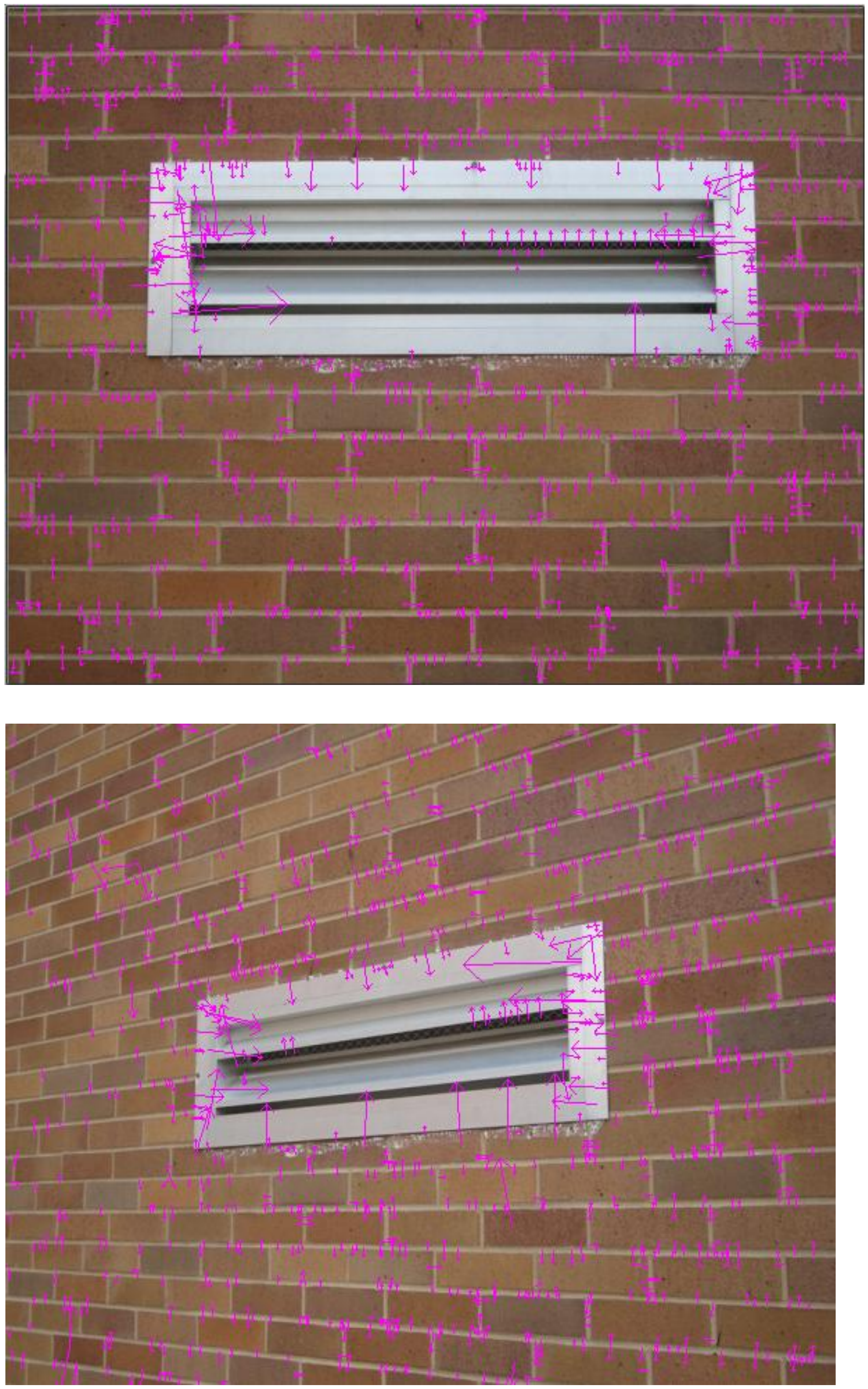


Figure 19. SIFT Features detected – Brick Wall Image Pair.

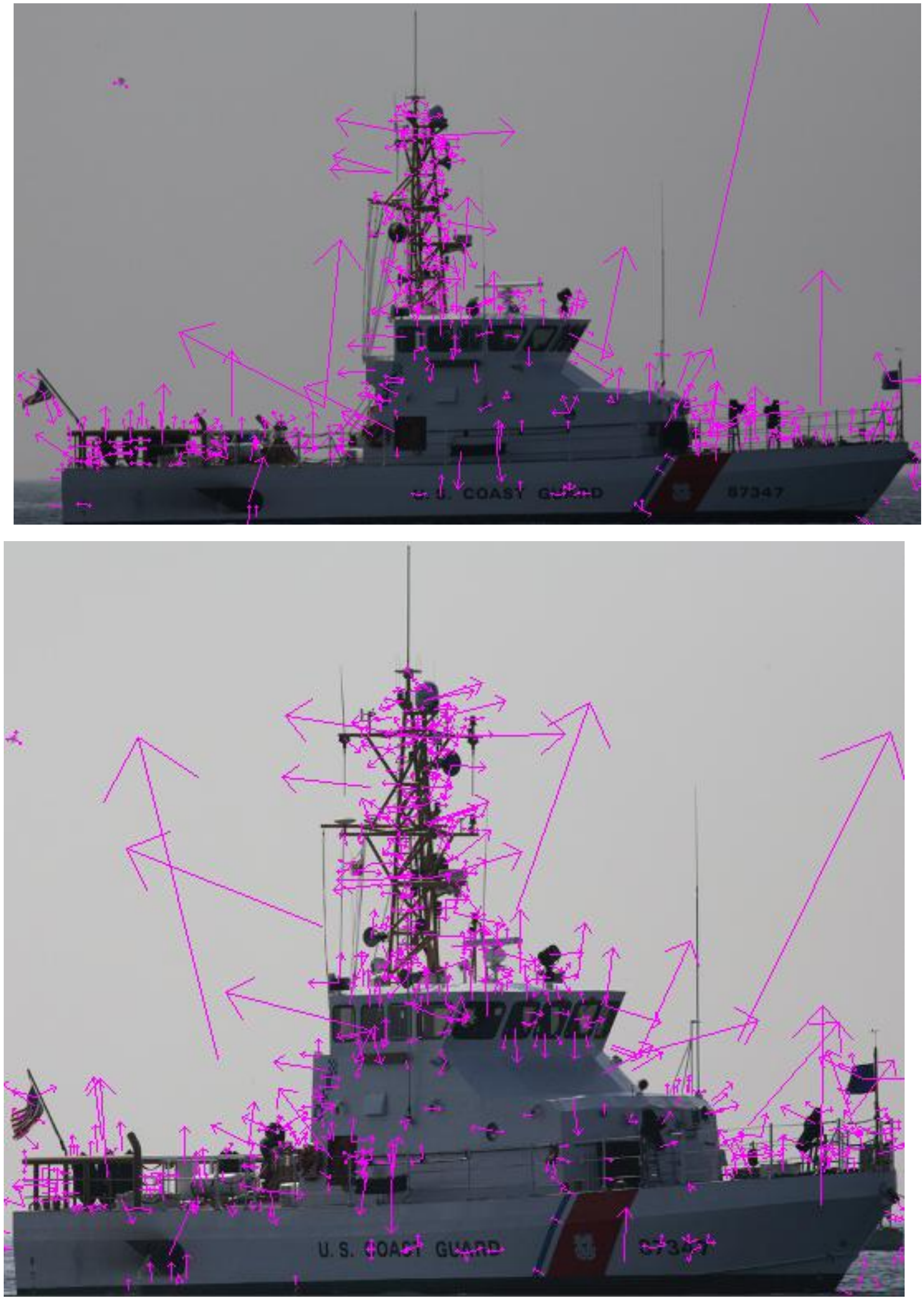


Figure 20. SIFT features detected – Boat Image Pair.

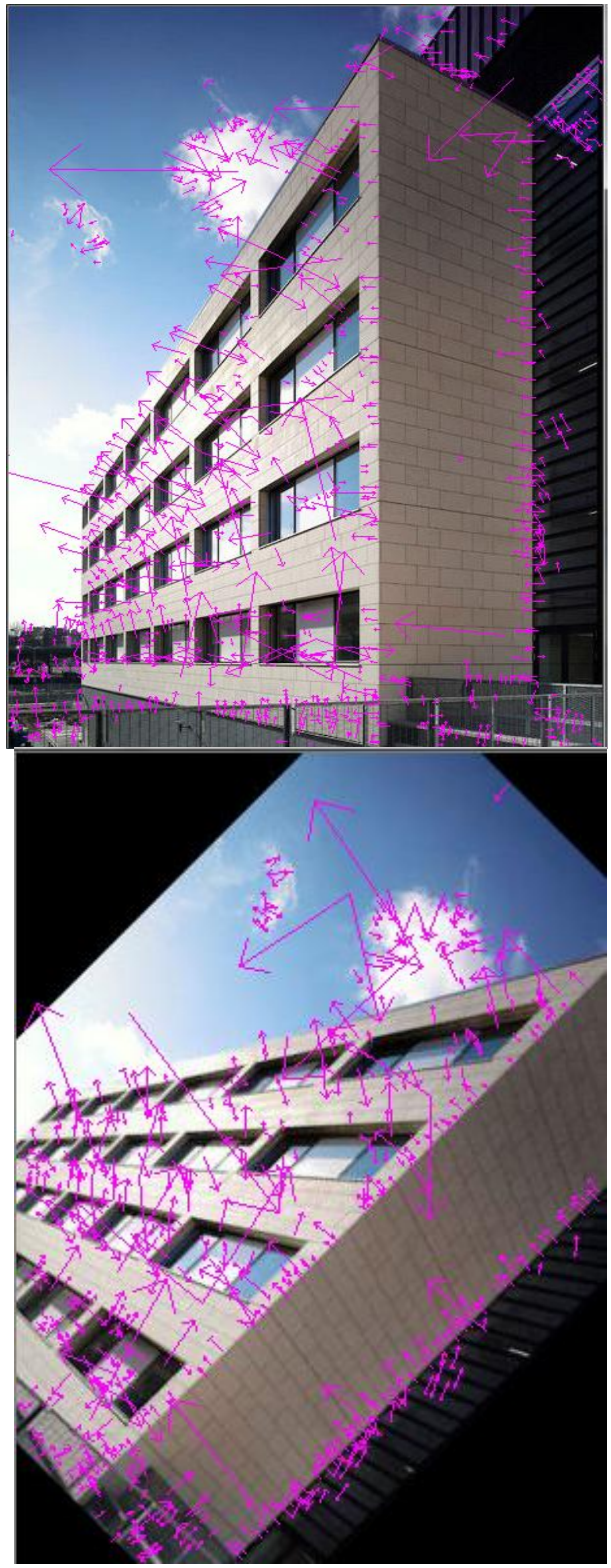


Figure 21. SIFT Features detected – Building Image Pair.

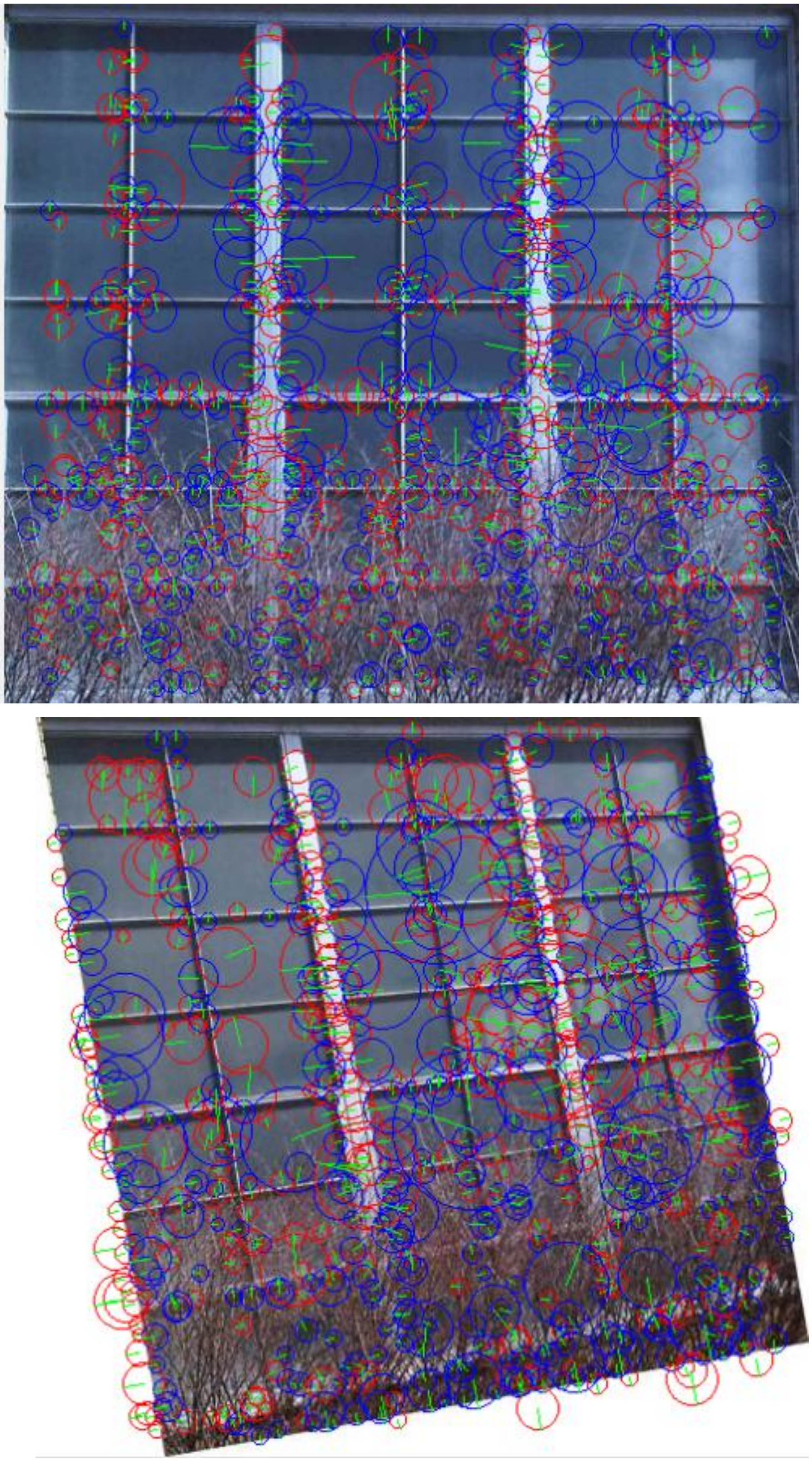
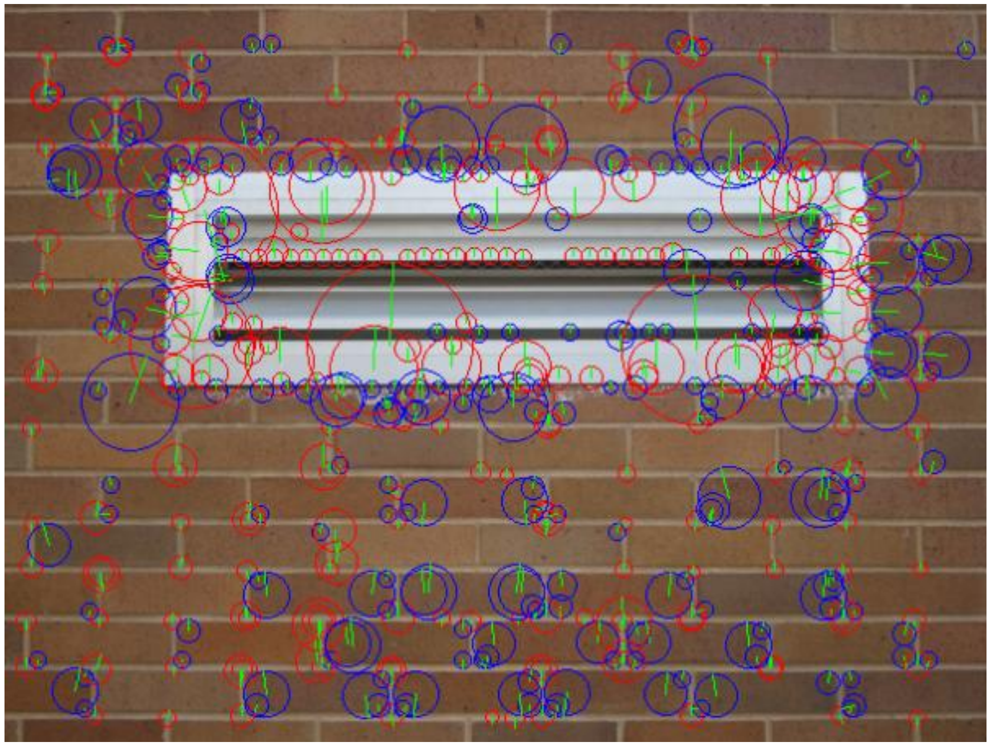


Figure 22. SURF Features detected – Window Image Pair.



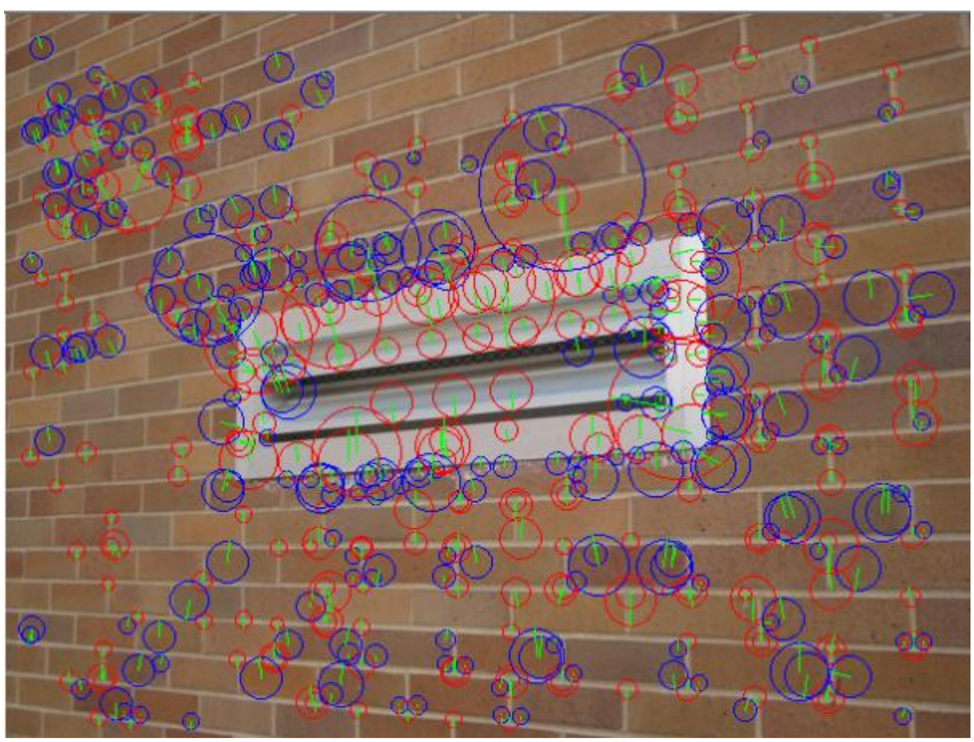


Figure 23. SURF Features detected – Brick Wall Image Pair.

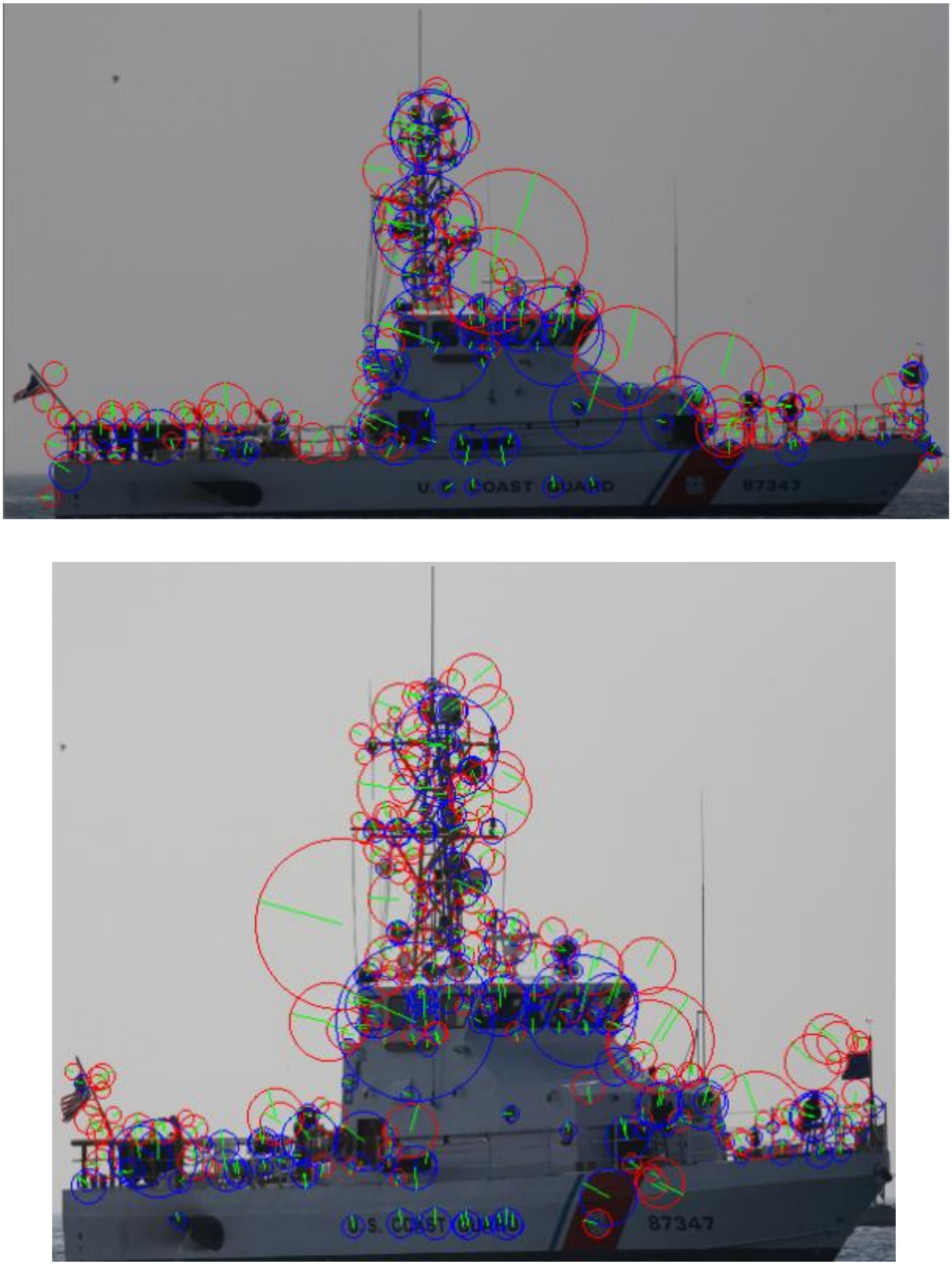
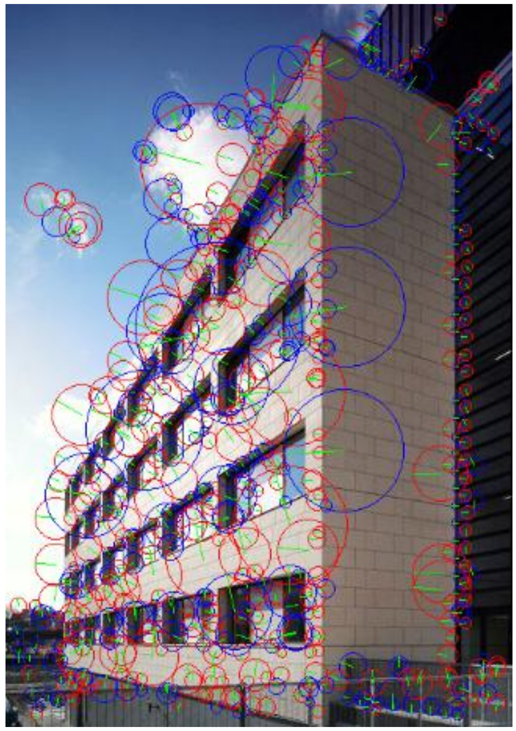


Figure 24. SURF Features – Boat Image Pair.



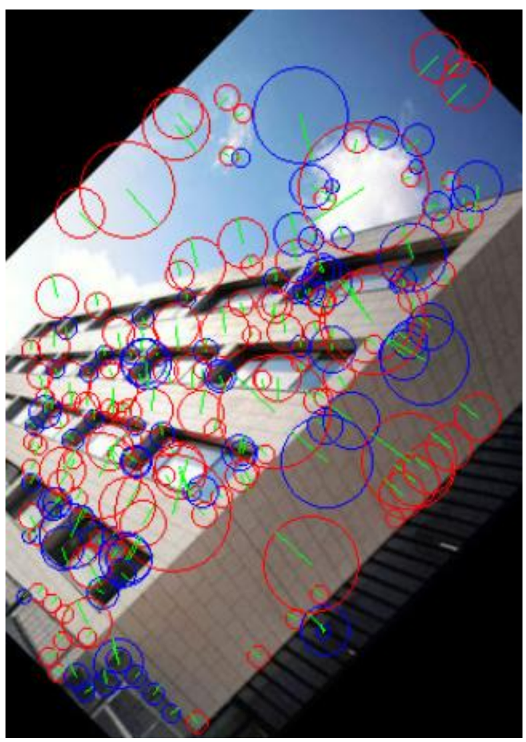


Figure 25. SURF Features detected –
Building Image Pair.

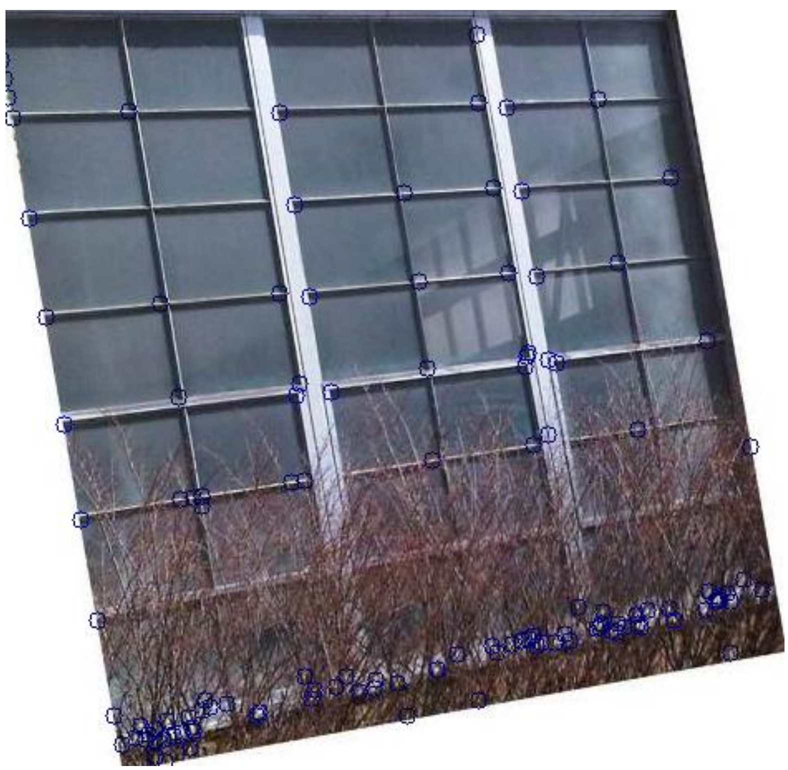


Figure 26. FAST Features detected – Window Image Pair.

Figure 27. FAST Features detected – Brick Wall Image Pair.

Figure 28. FAST Features detected – Boat Image Pair.

Figure 29. FAST Features detected – Building Image Pair.

Appendix B. Matches

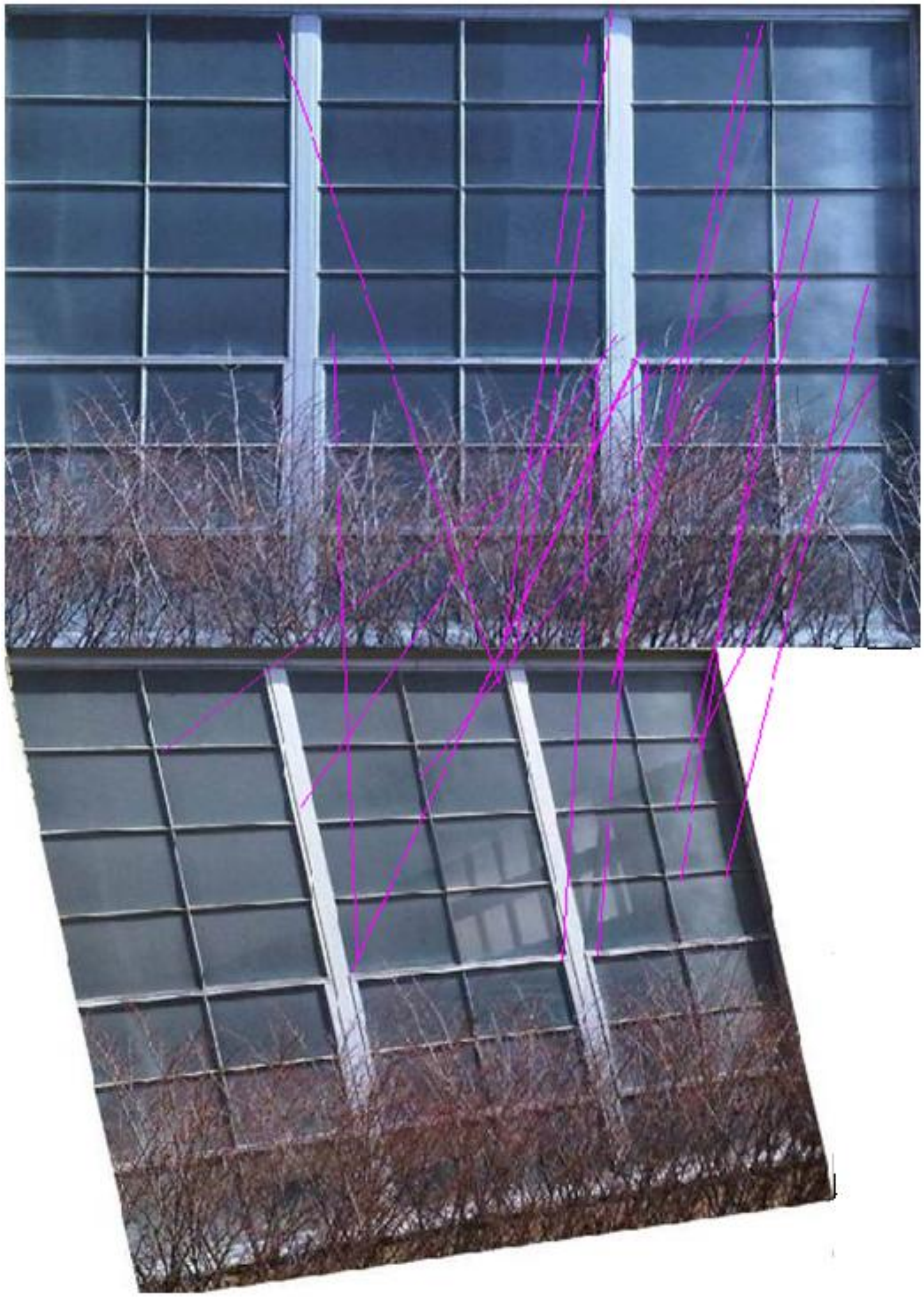


Figure 30. SIFT Matches – Window Image Pair.

Figure 31. SIFT Matches – Brick Image Pair.

Figure 32. SIFT Matches – Boat Image Pair.

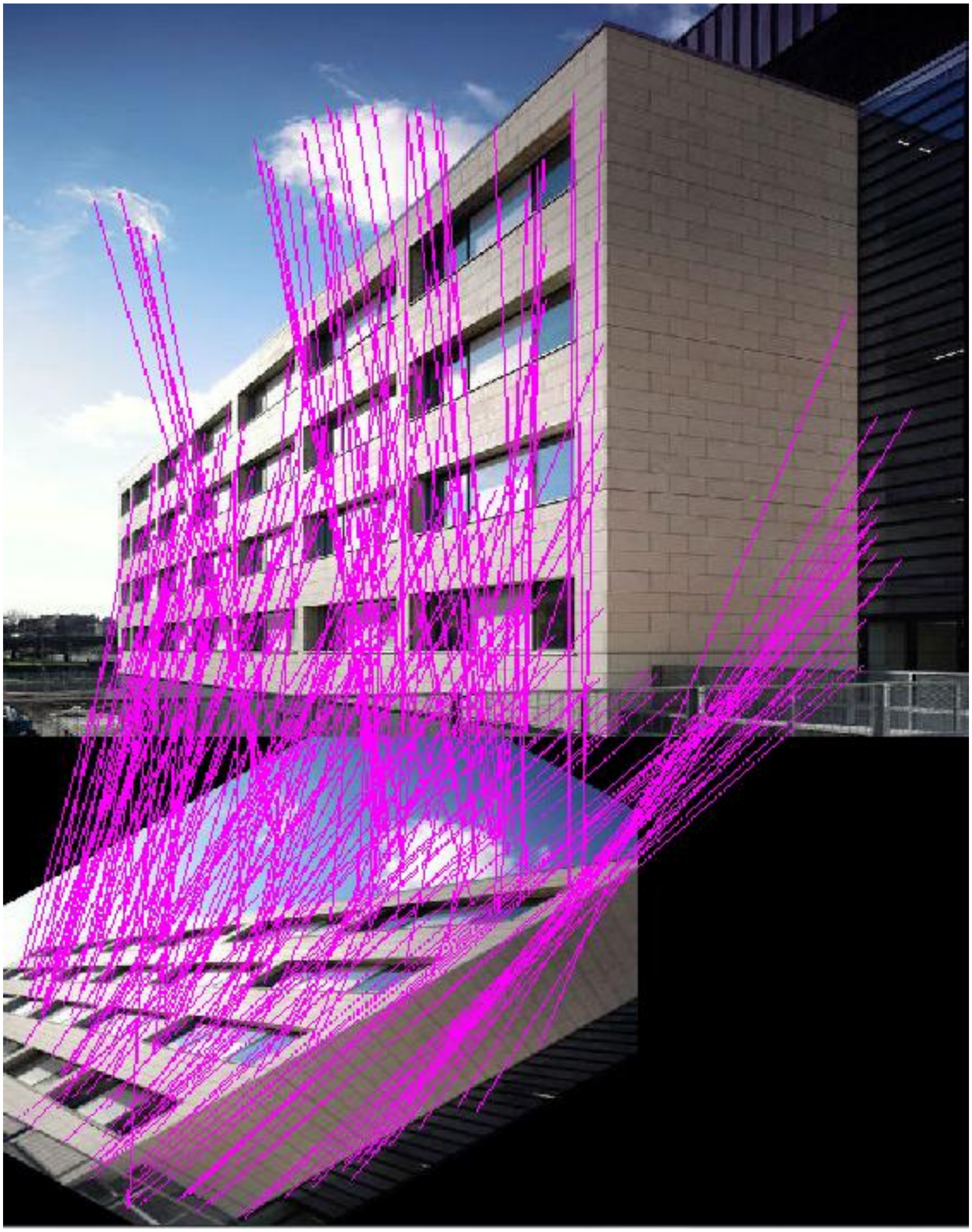


Figure 33. SIFT Matches – Building Image Pair.

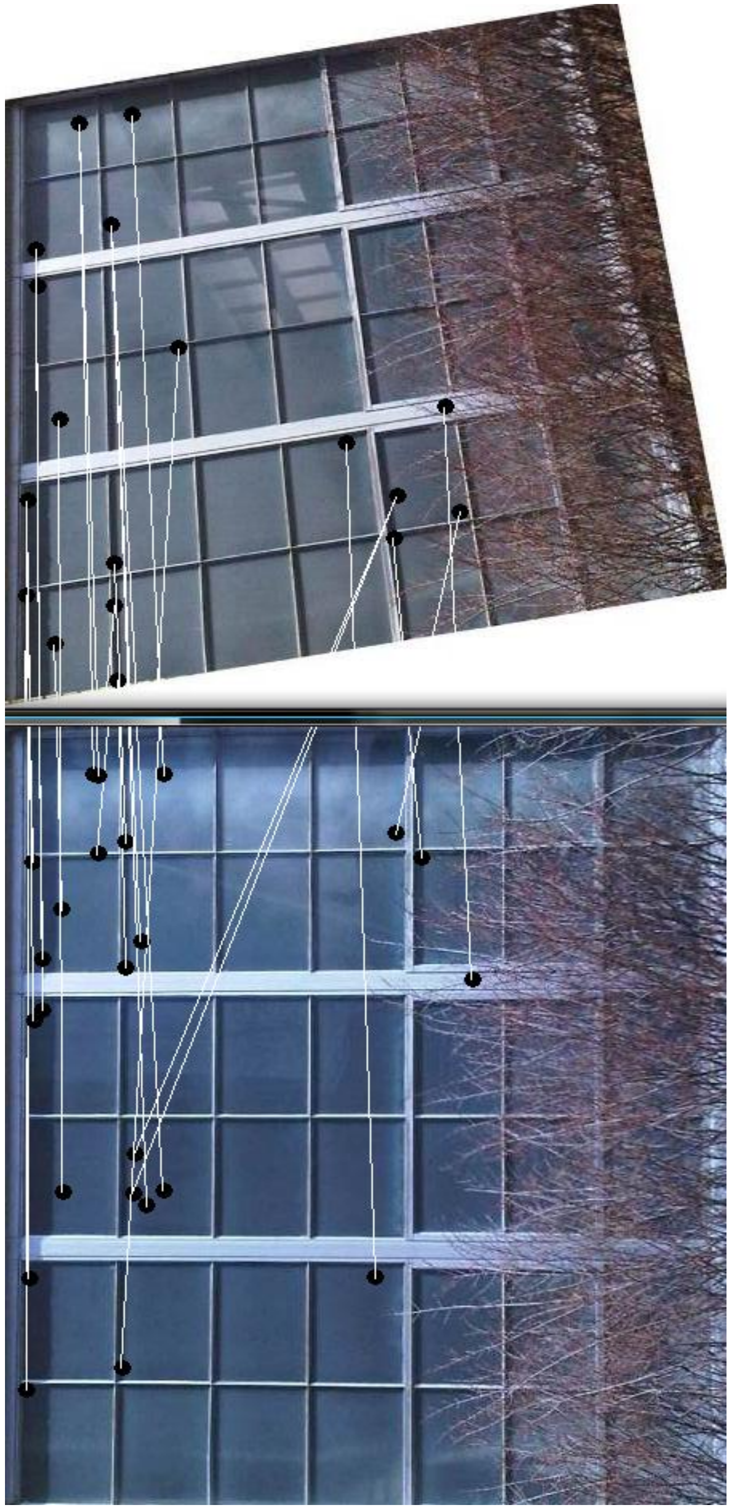


Figure 34. SURF Matches – Window Image Pair.

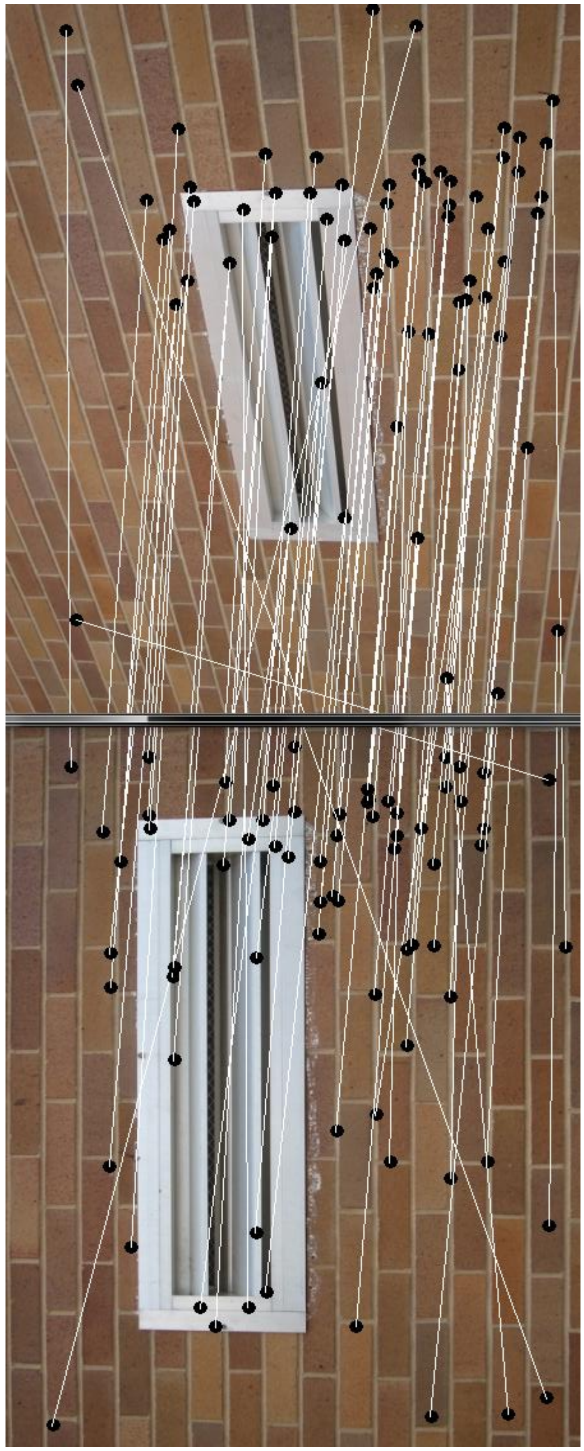


Figure 35. SURF Matches – Brick Wall Image Pair.

Figure 36. SURF Features for third pair – Boat Image Pair.

Figure 37. SURF Matches – Building Image Pair.

Appendix C. Matches found after threshold modification

Figure 38. SIFT Matches after reducing the threshold ratio from 0.49 to 0.35. Brick Wall Image Pair.

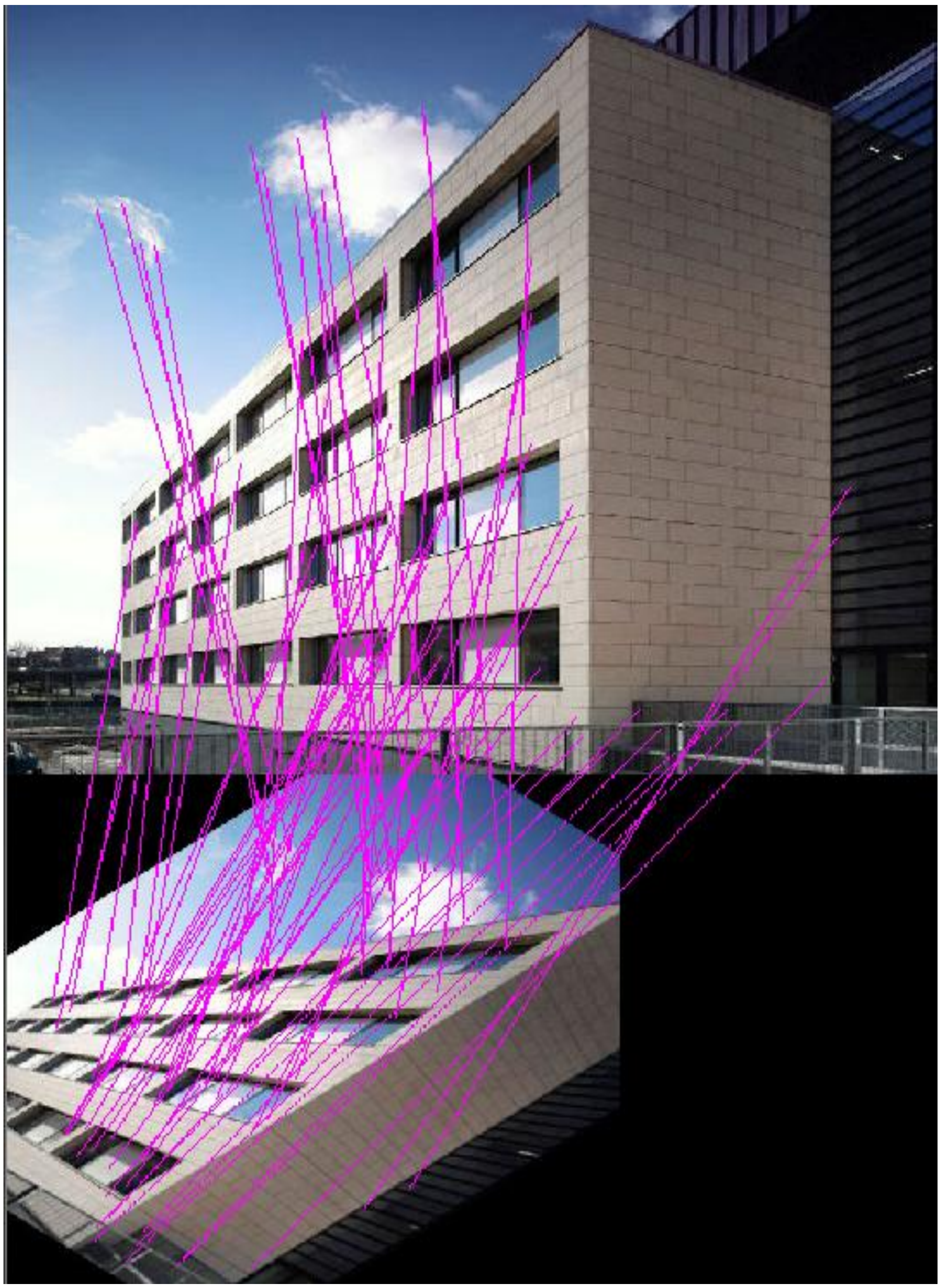


Figure 39. SIFT Matches after reducing the threshold ratio from 0.49 to 0.35. Brick Wall and Building Image Pairs.

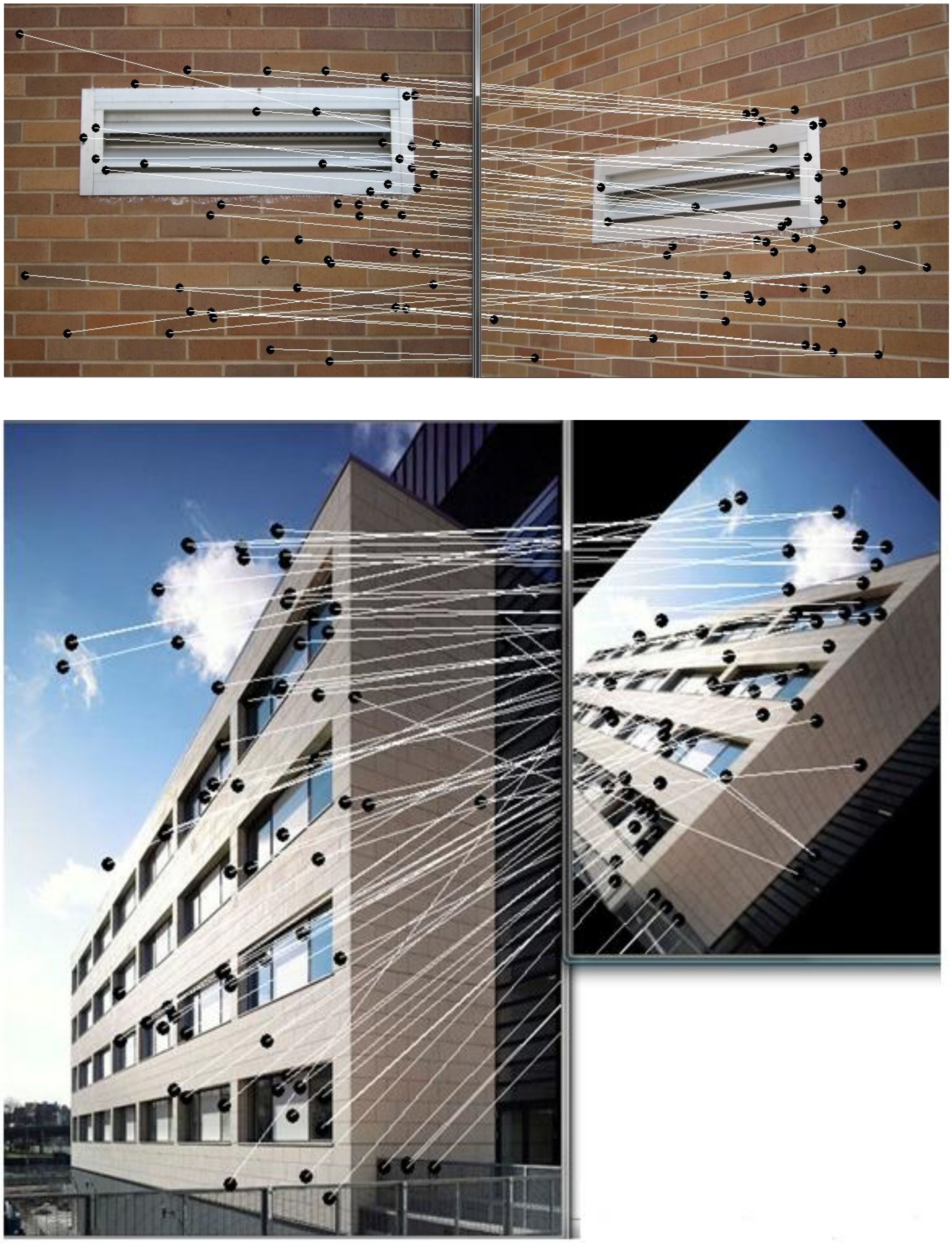


Figure 40. SURF Matches after varying the threshold value – Brick Wall and Building Image Pairs.

Appendix D. Type II error detection (Mismatches)

Figure 41. SIFT incorrect matches – Window Image Pair.

Figure 42. SIFT Incorrect Matches – Brick Wall Image Pair.

Figure 43. SIFT incorrect matches – Boat Image Pair.

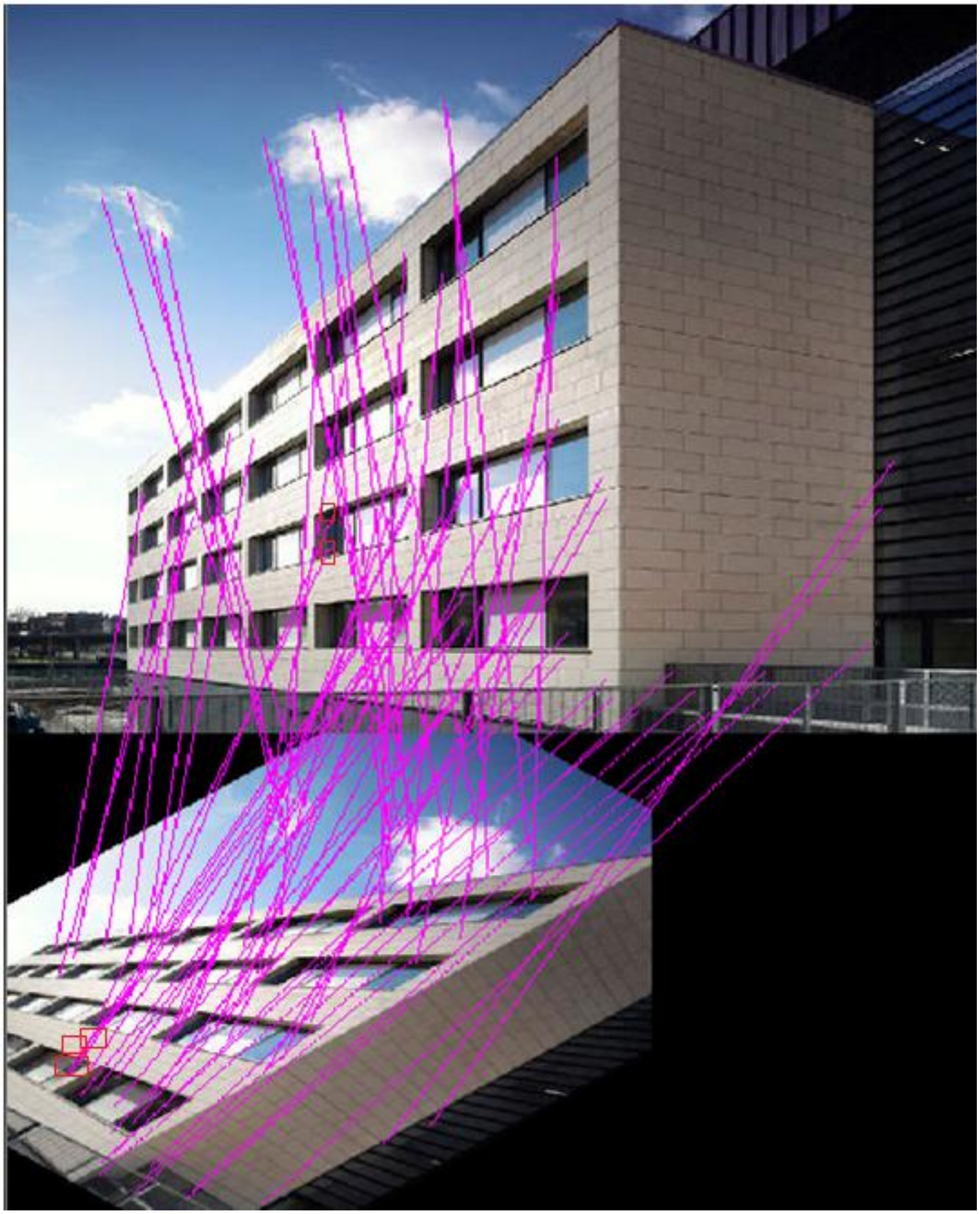


Figure 44. SIFT incorrect matches - Building Image Pair.

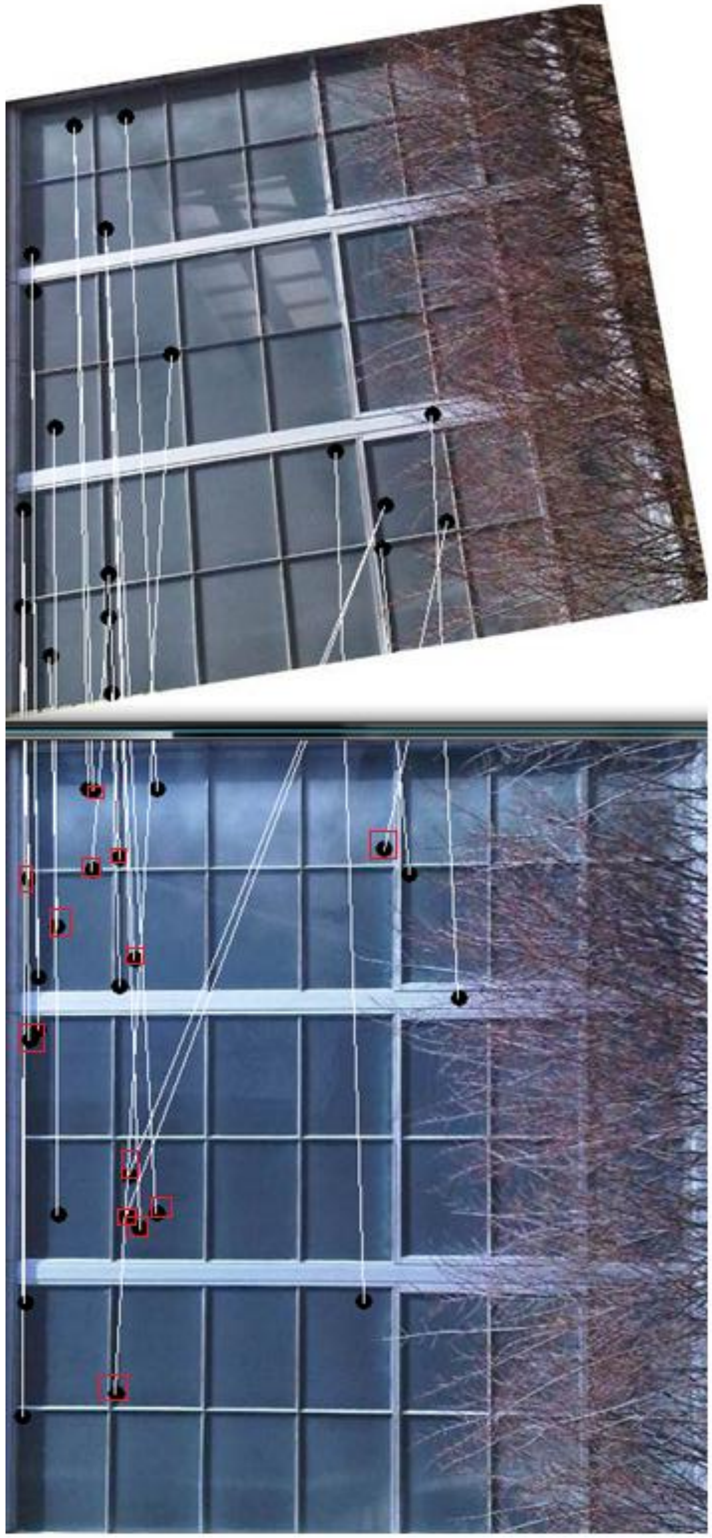


Figure 45. SURF incorrect matches – Window Image Pair.

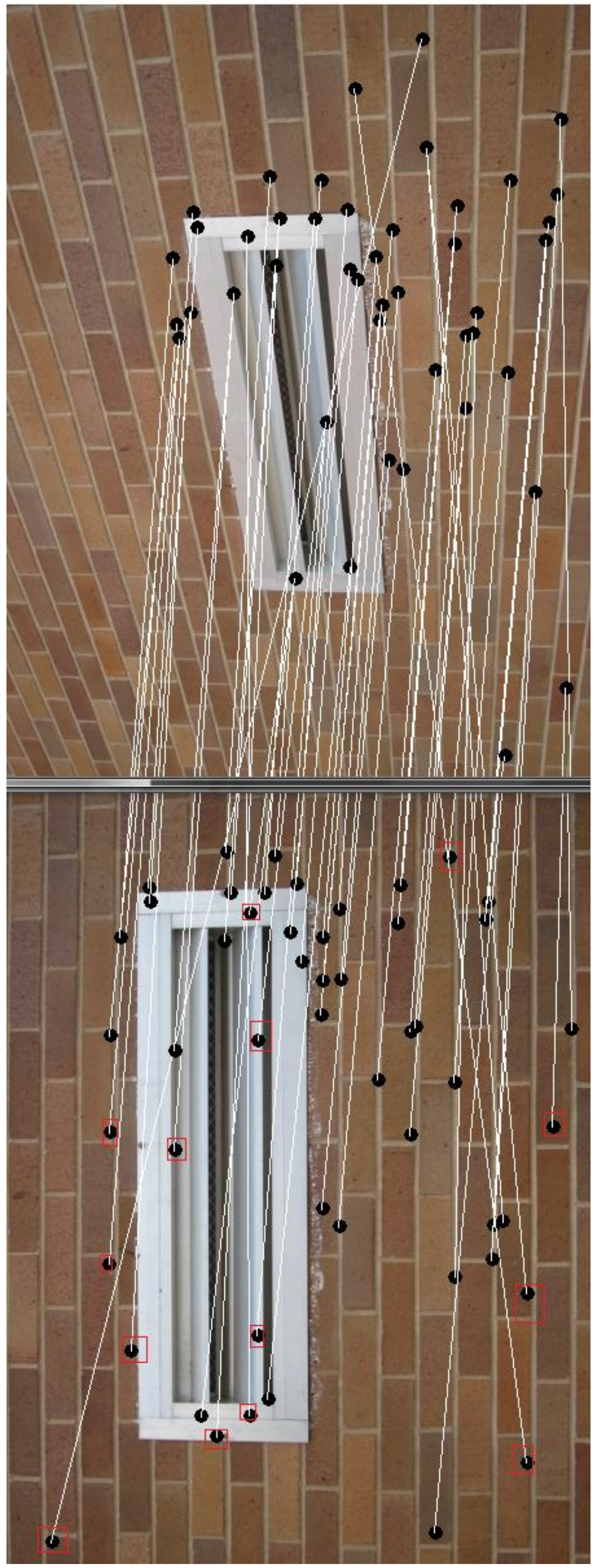


Figure 46. SURF incorrect matches – Brick Wall Image Pair.

Figure 47. SURF incorrect matches – Boat Image Pair.

Figure 48. SURF incorrect matches – Building Image Pair.

Appendix E. Manual matching for detected features

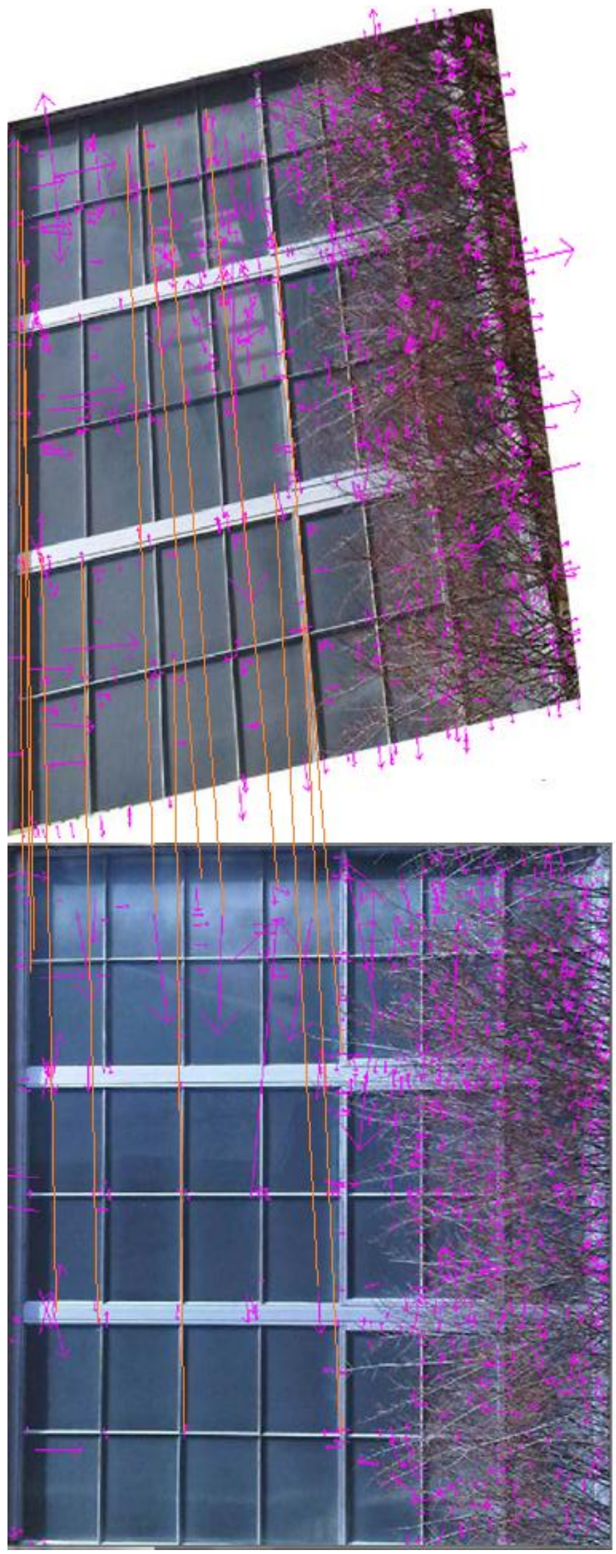


Figure 49. Manually detected potential matches for SIFT – Window Image Pair.

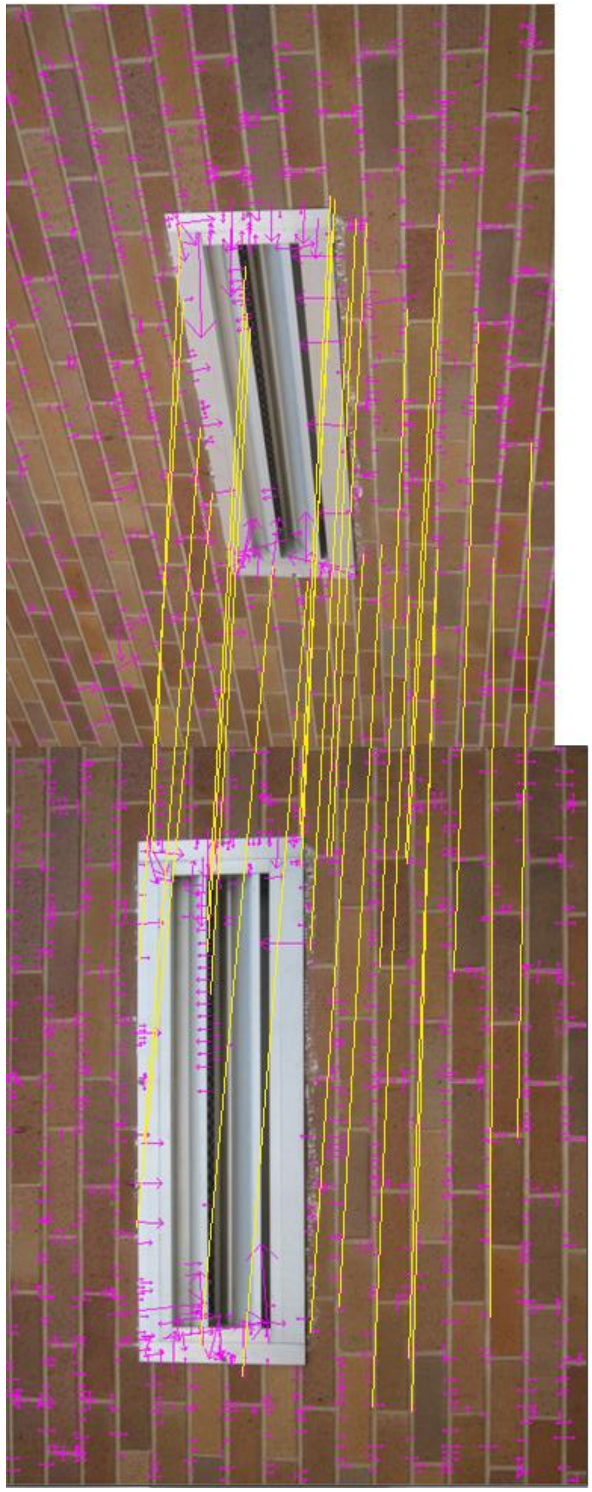


Figure 50. Manually detected potential matches for SIFT –Brick Wall Image Pair.

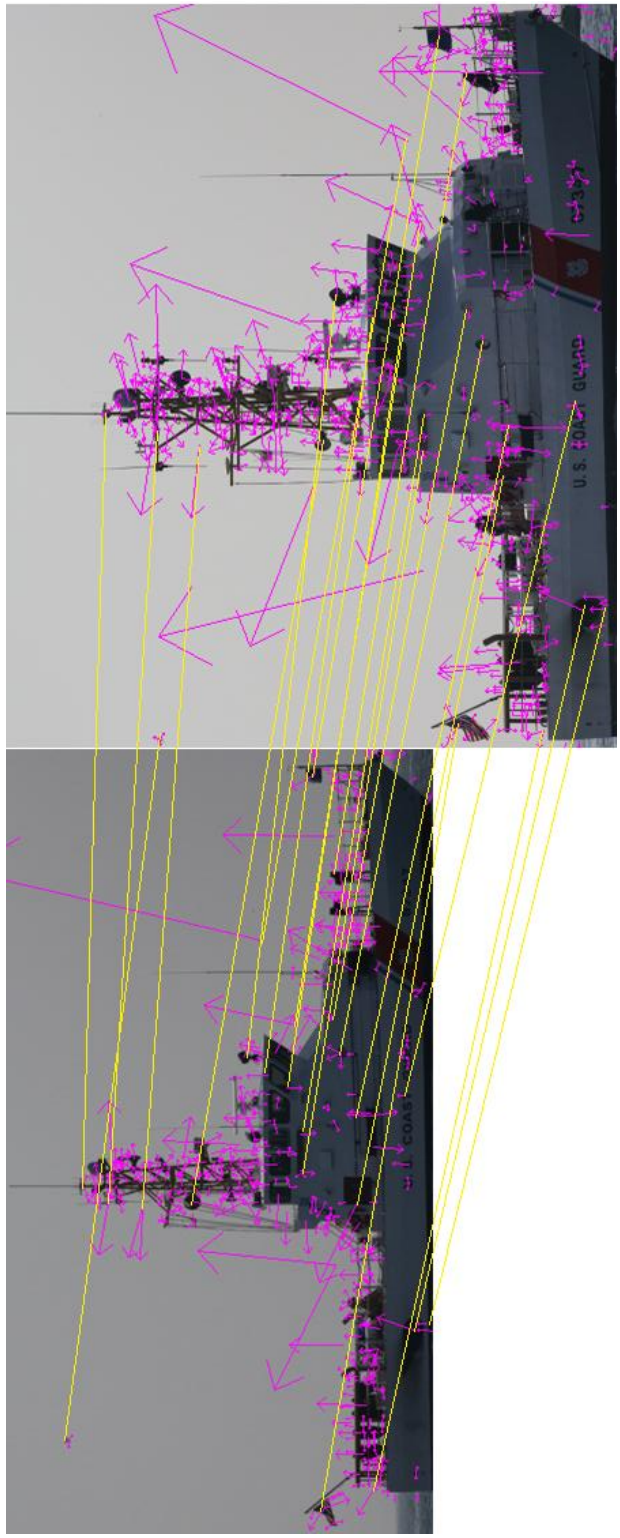


Figure 51. Manually detected potential matches for SIFT –Boat Image pair.

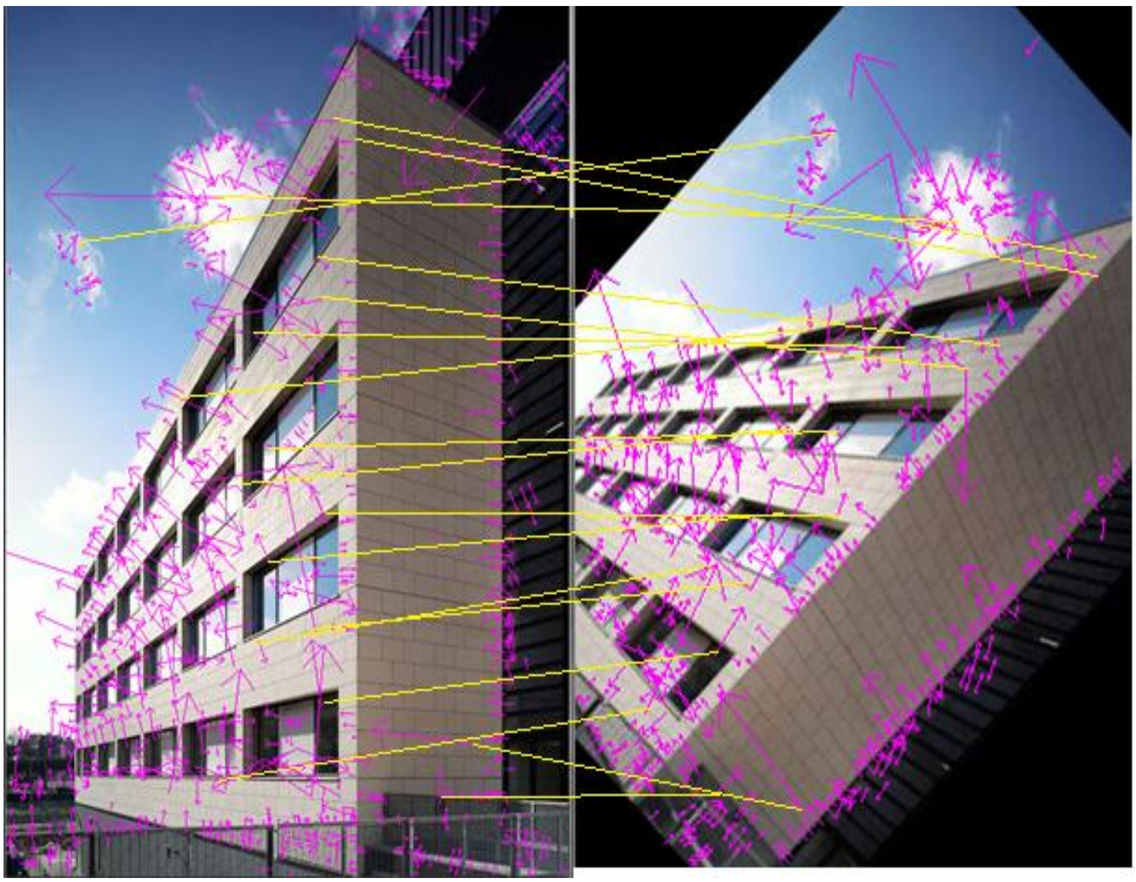


Figure 52. Manually detected potential matches for SIFT-Building Image Pair.

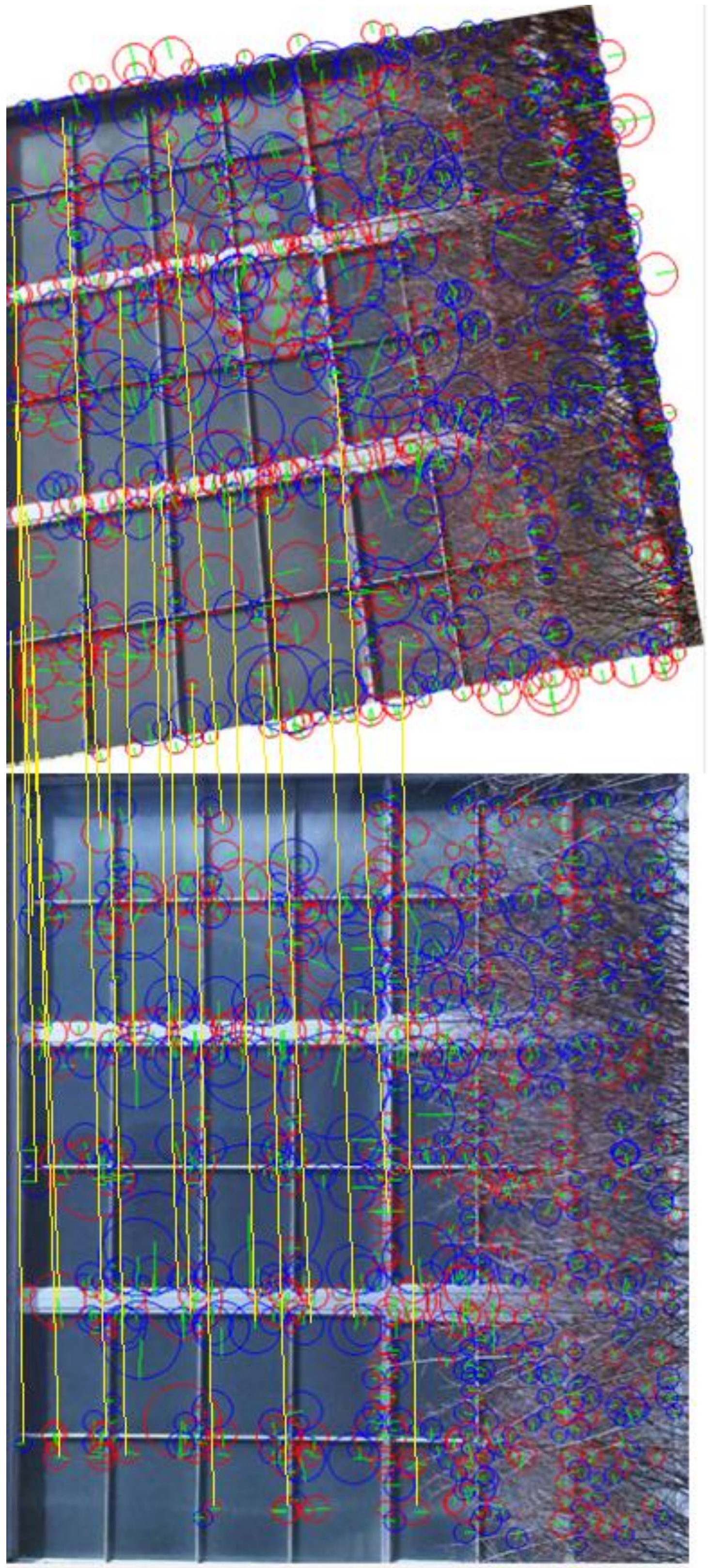


Figure 53. Manually detected potential matches for SURF-Window Image Pair.

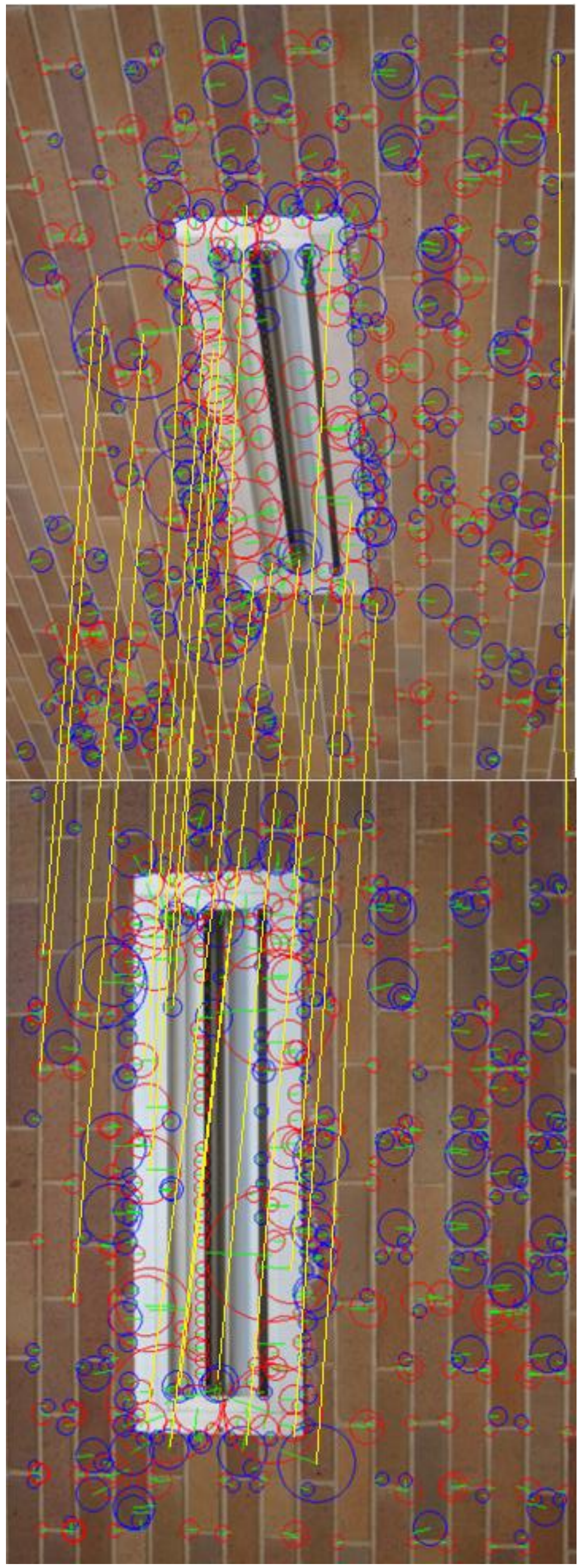


Figure 54. Manually detected potential matches for SURF – Brick Wall Image Pair.

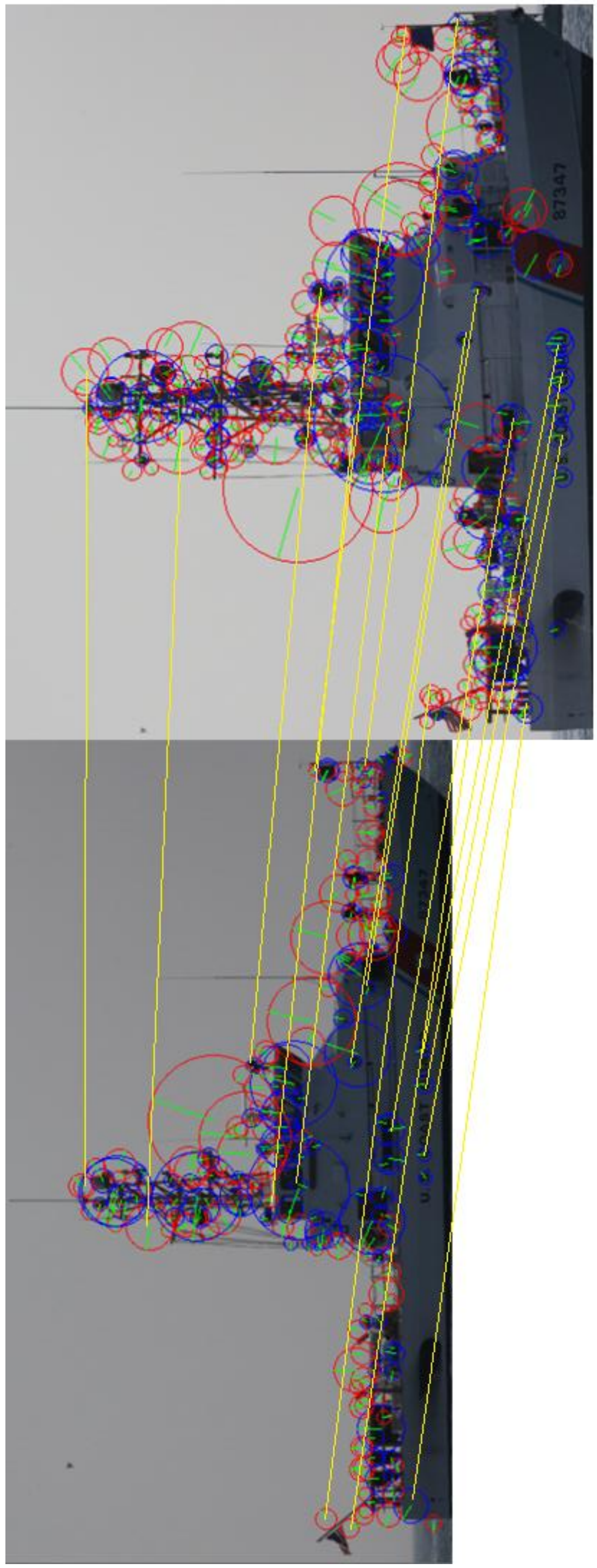


Figure 55. Manually detected potential matches for SURF – Boat Image Pair.

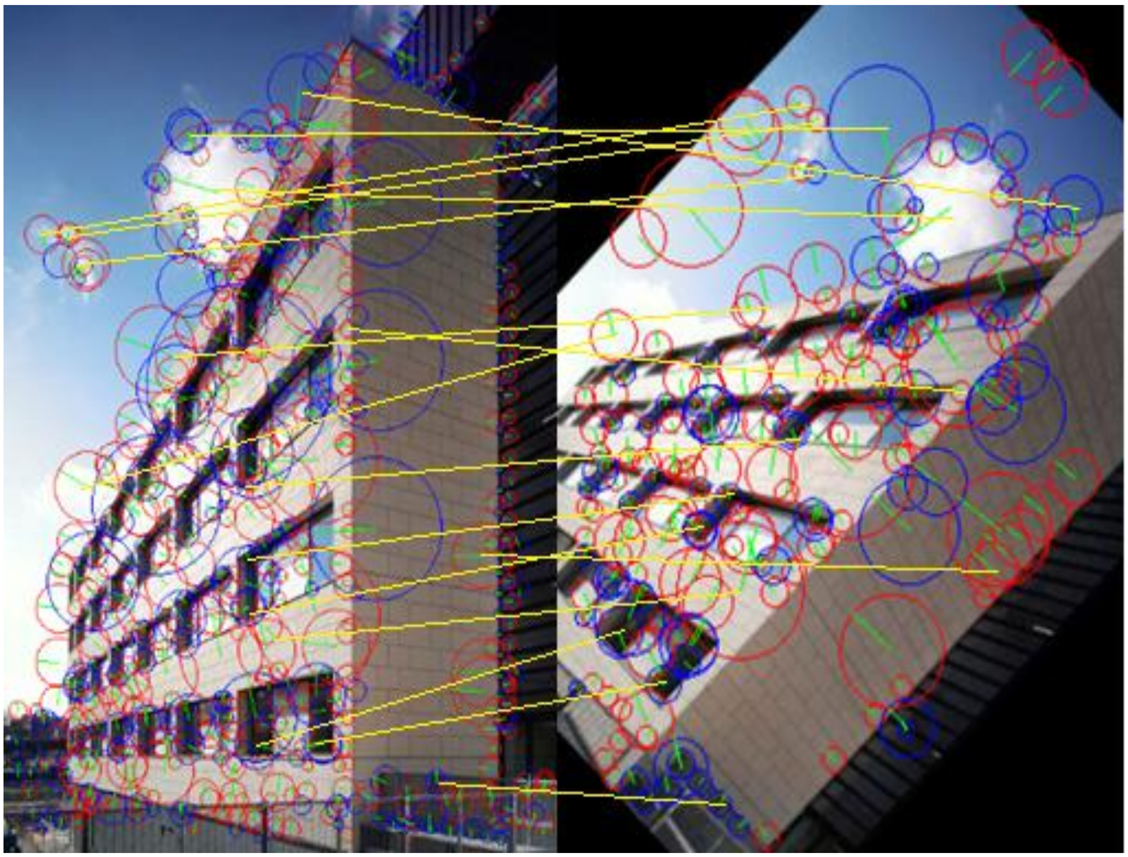


Figure 56. Manually detected potential matches for SURF-Building Image Pair.

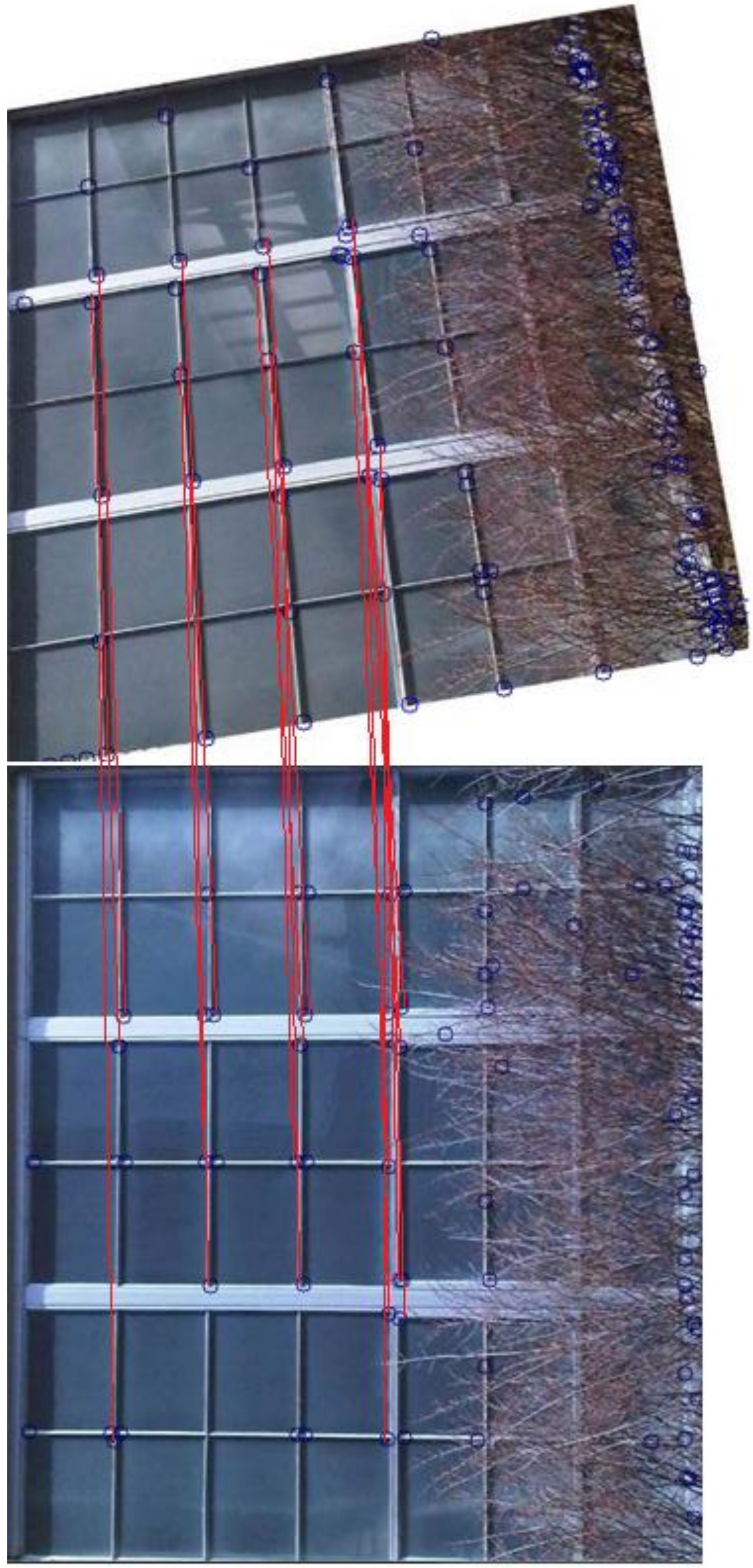


Figure 57. Manually detected potential matches for FAST-Window Image Pair.

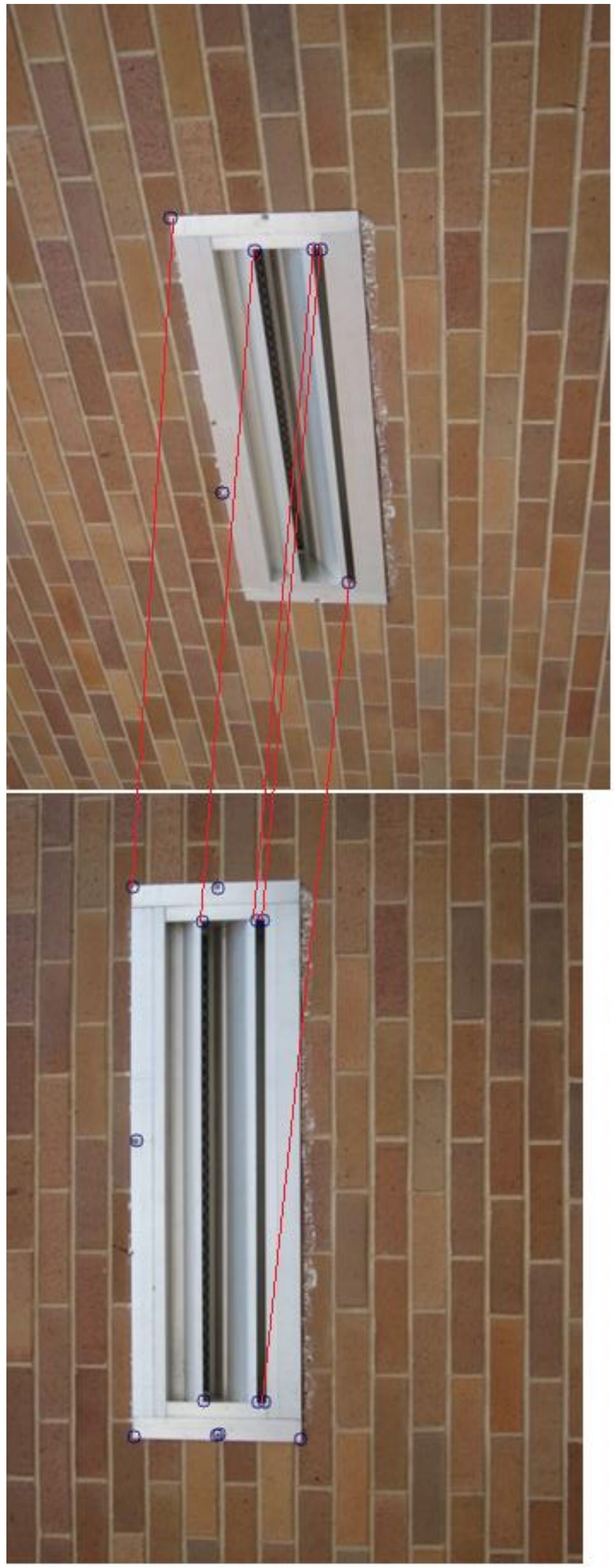


Figure 58. Manually detected potential matches for FAST –Brick Wall Image Pair.

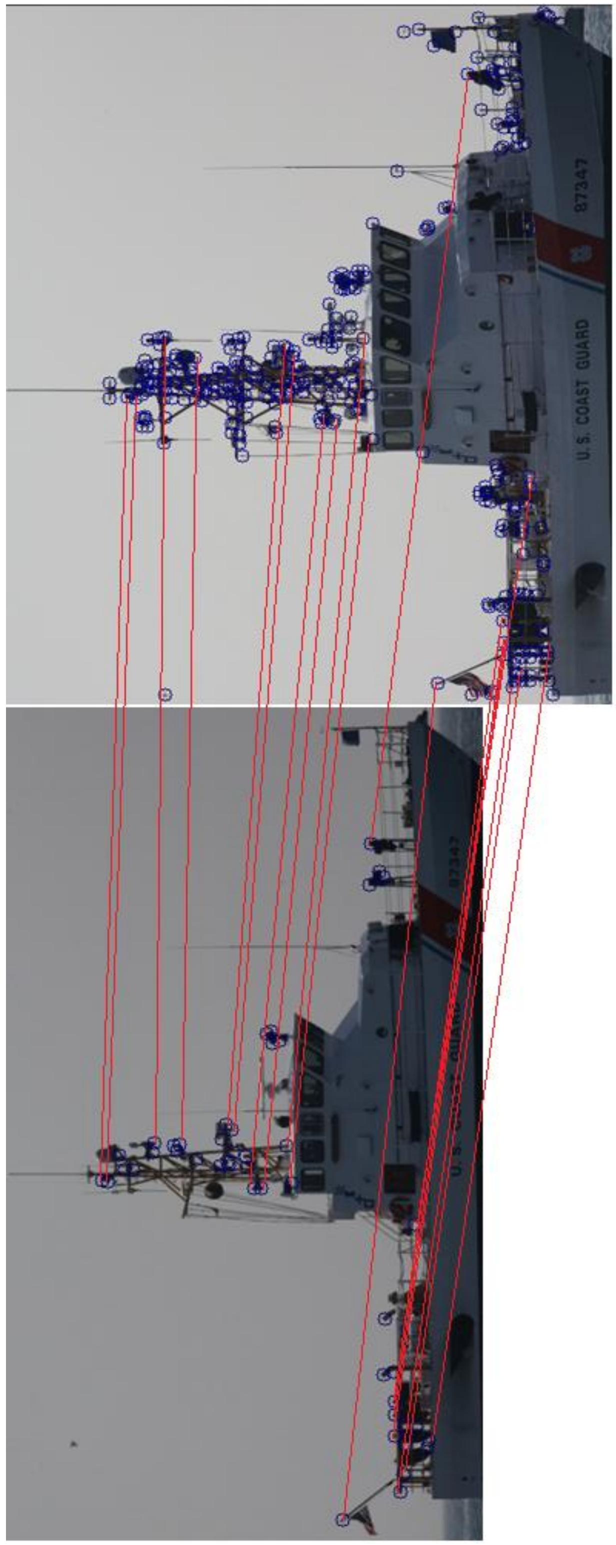


Figure 59. Manually detected potential matches for FAST-Boat Image Pair.

Figure 60. Manually detected potential matches for FAST-Building Image Pair.