Development and Analysis of Face Recognition System on a Mobile Robot Environment

Jit Shen Quah and Mariam Md Ghazaly*
Centre for Robotics and Industrial Automation (CeRIA),
Fakulti Kejuruteraan Elektrik (FKE),
Universiti Teknikal Malaysia Melaka (UTeM), Hang Tuah Jaya,
76100 Durian Tunggal, Melaka, Malaysia
* Corresponding author: mariam@utem.edu.my

ABSTRACT

In today's society, face recognition technology is widely used and applied in various fields such as biometric identification and security surveillance. However it is apparent that as technology advances, even more so in the direction of mobile robots such as a mobile security surveillance robot or a humanoid robot, the application of face recognition would need to transition from the traditional fixed position recognition to a mobile environment recognition as well. This research thus aimed at analyzing the performance of face recognition algorithm performance in a mobile environment as compared to a static environment. This is done via integrating a developed face recognition software onto a mobile robot in terms of image captured distance and in extension its accuracy during static and dynamic conditions. The results from this research shows that when there is an increase in mobile robot speed from 0 ~ 65% duty cycle there seem to be a reduction in performance in terms of range of capture of approximately 30% for both face recognition and face identification which is a clear reduction in performance. From the results as well, the optimum speed for the mobile robot to move to obtain optimum performance for both recognition and identification was found to be at 60% PWM with minimum neighbors and scaling factors both set to 1.

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Introduction

The main motivation of this project is to find out the performance of face recognition systems under mobile conditions. This is important because currently, majority of face recognition techniques are developed in a stationary and static environment such as the methods proposed by Marcus et al [1] for a Part-Based Representation and Classification for Face Recognition or one by Barrah et al [2] for a new face recognition technique based on singular value decomposition or perhaps one by Guo et al [3] which propose a method of face recognition based on convolution neural network and support vector machines all of which again are advancements in face recognition techniques but is done in a static environment.

While yes, it can be said that these methods are then applied to mobile robots to do various functions such as a multimodal biometric identification system for mobile robots combining human metrology to face recognition and speaker identification proposed by Ouellet et all [4] or a simple mobile robot controlled by face recognition proposed by Alexandru et al [5], there is however a common similarity between both projects which are the face recognition process is done either during subject and robot is stationary[4] or either subject or robot is moving at low speeds (2 rad/s)[5][6].

The reason for this handicap is mainly because of motion blur. Motion blur is the degradation of sharpness, brightness and contrast of image leading to the loss of high frequencies due to the object moving when the image was taken [7][8][9]. This is a major issue for face recognition system because most recognition program such as Eigenface method does face recognition via detecting the face outline of the face first then scaling the outline to the fix image scaled size and then followed by comparing the variations in distance between points plotted on the face [10-12] thus if the the face of the subject is distorted due to motion blur, the system would misrecognize the subject.

As technology advances, there is an emerging trend of technology development which requires the usage of face recognition on mobile robots [13-14] and while they could design the robot to slow down/stop to identify, this would slow down the general operations of robots with surveilence or security functions such as [15]. Thus again it is important to understand/map out the general effects of speed towards face recognition in a mobile robot environment for the references of future projects/researches.

The method chosen for face recognition in this analysis is the Eigenface method from the OpenCV library. Eigenface method works by treating grayscale images as vectors spaces with corresponding intensity levels. By treating images as sample data, it is then possible to perform Principle Component Analysis and obtain the eigenvectors which makes up the basis of vector space. These eigenvectors on the other hand become representation of the strongest characteristics of the face in the data set and it is this data that is being compared with when another unknown face is being recognise. Although

other methods of face recognition exist which in some ways are much more capable in the sense that it is able to solve issues regarding speed of identification [16], recognition under varied lighting [12], as well as varied posture and facial expressions [17-22] than the chosen method, in the end the chosen method was still chosen due to the limited hardware capability in terms of storage space for operations as the advance methods also comes with higher storage usage.

Mobile Robot System Design

For the setup, a mobile robot was designed and developed as a platform to carry an onboard Wi-Fi camera which in turn would relays back all information back to a central computer which will do both the processing and the sending of commands to the robot in question as seen in Figure 1.
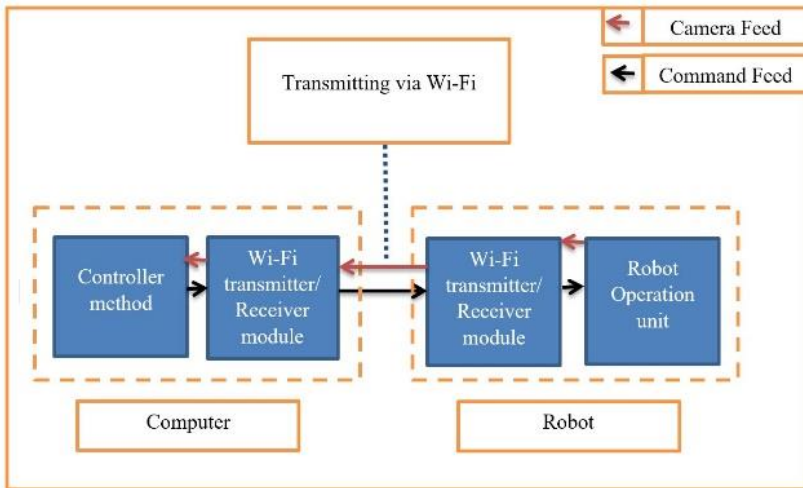
Figure 1: Function diagram depicting the basic operation of the robot

The robot movement was controlled using an Arduino uno connected to an Xbee S1 unit which will receive instructions from the command centre and then relay it to the Arduino uno to be translated into a movement. A few methods of control can be used for the robot as long as the device is connected to the local Wi-Fi emitted by the Xbee S1 unit. In the case of this project, a phone app was used to control the manual movement of the robot which can be seen in figure 2.

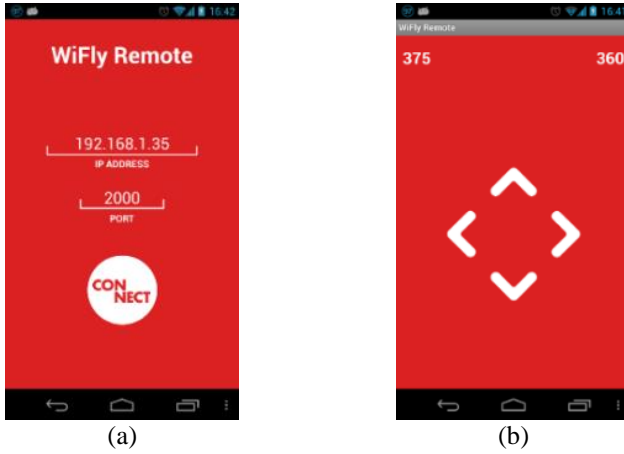(a)   (b)

Figure 2: (a) Phone app connected to local Wi-fi, (b) Control console for phone application

The robot itself comprise of two Planetary DC Geared Motor (IG32E-264K) attached to a mobile robot base. The motors are initiated via a 4-channel motor driver which in turn is initialized by an Arduino Uno which receives its commands as mentioned previously from an Xbee unit which is communicating with the main computer or phone app. A simple web camera is attached on top of the base and is connected back to the main computer. Finally, the robot itself is powered by a 12v 500mAH power bank whereas the motors are powered separately by a 12vdc 1.2AH lead acid battery. The hardware can be seen in figure 3.
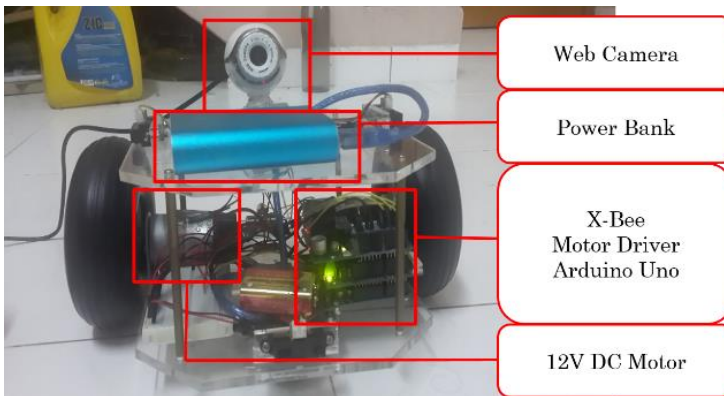

Figure 3:Assembly of mobile robot hardware

Central Computer System Design

The central computer which acts as the main processing unit for the system as well as the command centre for the robot. The system was made using Microsoft Visual Studios C# with the aid of emguCV for the face recognition application. The final outcome can be seen in Figure 4 has three on board parameters which can be changed at any given time. These are the scale increase rate, which is the rate where an identified image is identified for the process of recognition, the minimum neighbour, which talks about the number of detection's required within a close proximity for it to be registered as a positive detection and finally the minimum detection size, which is the smallest detection possible on the frame. In the minimum neighbour detection setting, 0 would means that as long as there is a detection then it is considered a positive detection, whereas 3 would mean the system would need at least 3 detections in the same vicinity for it to be classified as a positive detection.
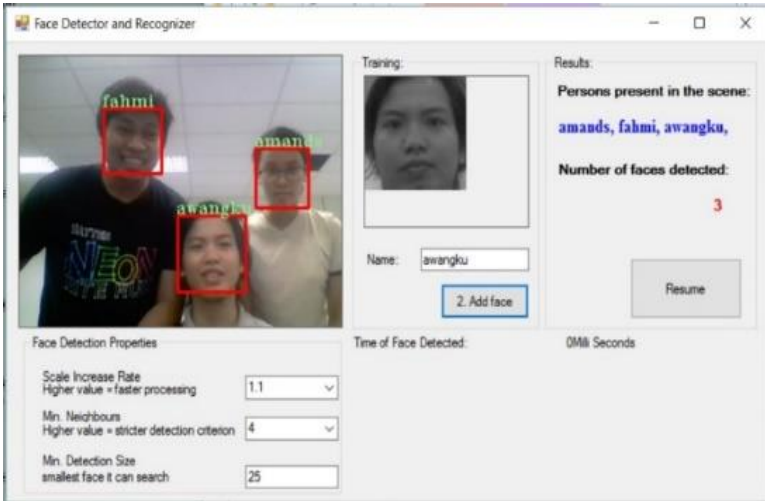

Figure 4: Central Computer Interface

The operation of the central computer system can be seen in Figure 5.The central computer will first receive the input from the on board web camera and its image will be filtered with a face identification mask using the viola-jones method which will identify the precense of faces within the captured image itself. Once the face is identified, it will be put through a face recognition mask using PCA Eigenfaces method to be recognized.
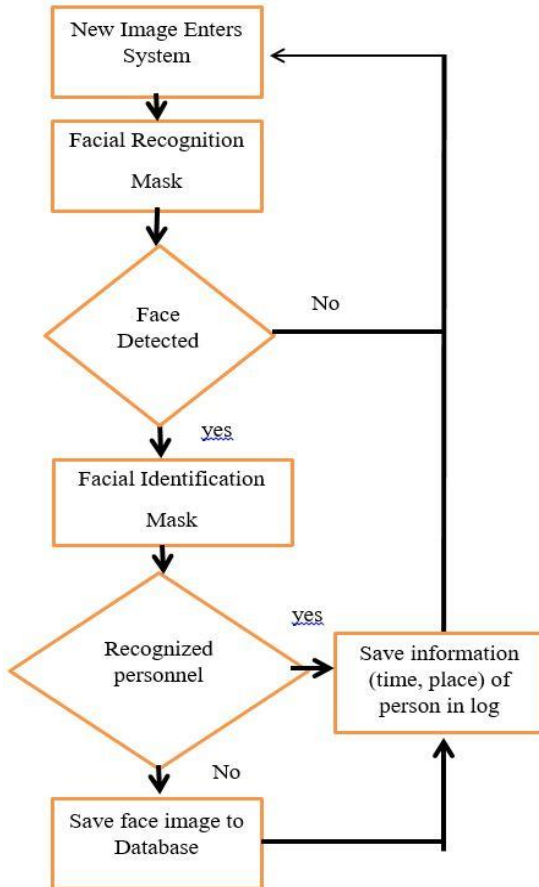
Figure 5: Figure showing final function of the developed software

If the face is recognized, a number,the face with its owner as well as the date and time which is determined by the date and time of the central computer is saved to a log for ease of future reference as seen in Figure 6. The same process is conducted if the face is registered as unknown with the exception that there will be no name assigned to the picture.
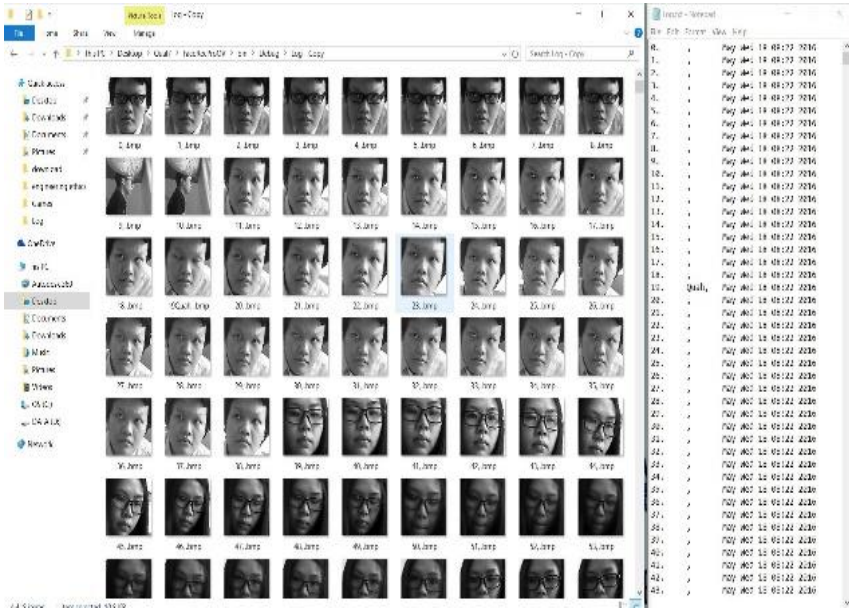
Figure 6: Log of capture faces with time and date of capture

4.0 Research Experiments

Effective Range for Face Identification and Recognition in a Mobile Environment vs. static environment

The goal for this experiment is to find out the effective range for the camera to perform face recognition and face identification. Face identification is the step that is done prior to face recognition which means to say the goal of face identification is merely to identify if there is a face within the scene whereas in recognition the goal is to identify the identity of the owner of said face. For both face recognition and face identification, the steps would be similar where the first step is to set up the experiments as seen in figure 7. The subject is a person that will stand a certain distance perpendicular to the camera where the centre of the camera screen is position to the centre of subject. The camera is found to have the area of vision of 14.36° from the mid section per side resulting in the total area of vision of 28.72°
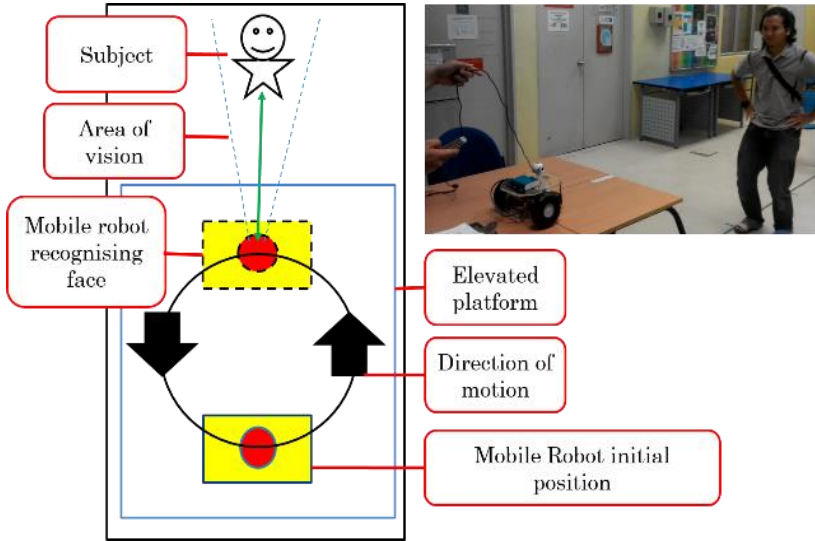
Figure 7: Experiment setup face recognition and identification experiments

For the first part of this test which is the experiment for face identification, the subject is asked to move backwards in a 1m interval until the camera is no longer able to detect the person face (red box no longer present of subject face) or if there is too much error in detection (as seen in figure 8(c)). The maximum and minimum range of capture for each subject with its corresponding parameter is taken, averaged out and then tabulated. The experiment is repeated for each parameter that are scaling factor and minimum neighbour for each subject for varying levels of PWM setting. The PWM value was adjusted from 0% to 100% at a 10% interval where the robot will rotate on a fixed axis and its camera is static throughout the experiment as seen in Figure 7. At 100% PWM, the robot moves at approximately $3.8ms^{-1}$ and every reduction of 10% in PWM input represents a drop of $0.4ms^{-1}$ from its maximum speed.

For the second part of this test which is experiment of face recognition, similar to the first, the subject is asked to move backwards in a 1m interval until the camera is no longer able to identify the persons face (name of the person no longer apears on the box as seen in figure 8(b)) or if there is too much error in detection (as seen in figure 8(c)). The maximum and minimum range of capture for each subject with its corresponding parameter is taken, averaged out and then tabulated. Experiment is then repeated with varying face identification parameters such as scaling factor and minimum neighbours and then again with different subjects with varying features and finally again with varying PWM from 0% to 100% at a 10% interval where the robot will rotate

on a fixed axis and its camera is static throughout the experiment as seen in Figure 7. Again. At 100% PWM, the robot moves at approximately $3.8ms^{-1}$ and thus every reduction of 10% in PWM input represents a drop of $0.4ms^{-1}$ from its maximum speed.
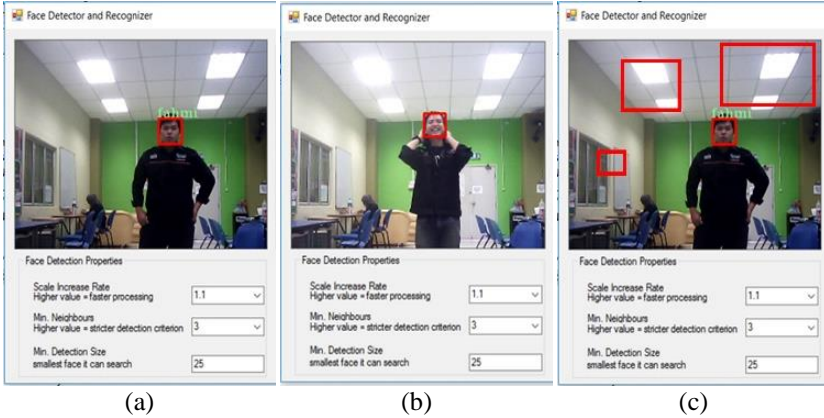

| (a) | (b) | (c) |

Figure 8: Figure showing 3 states of detection (a) System Accurately recognition subject, (b) System identified but failed to recognize subject and (c) System unaccuracte identification .

For both parts, subject will move until the system is either no longer able to recognize the subject as seen in figure 8(b) in the case of recognition or if the box is no longer present in the case of identification or if the detection becomes highly unaccurate as seen in figure 8(c). In both cases, subject is asked to take a step foward and then repeat the steps backward to ensure it is not a random error. If the error repeats itself then the sytem is considered have failed to detect.

Results and Discussions

Static Range Experiment for face recognition and identification

In a static environment, it would seem that small changes in scaling factor as seen in Figure 9 does not really affect the performance of the face identification software. This lack of effect between the scale factor parameter and performance of face identification in a static environment can be seen using the standard deviation for its range of capture. The value obtained from that is an average standard deviation of 0.23m, which is insignificant. This was an expected result, Scale factor corresponds to the rate of which images are taken and compared with positive identification. A higher scale factor here would

indicate a higher delay in between frames being sent to the system for identification. In this regard, as objects are static and in an ideal format for image gathering, reducing the frequecy of images being sent to the system for identification does not affect the chances of a person being identified and thus why there is little to no visible affect when varying the scale factor and observing its affect to the range of capture.
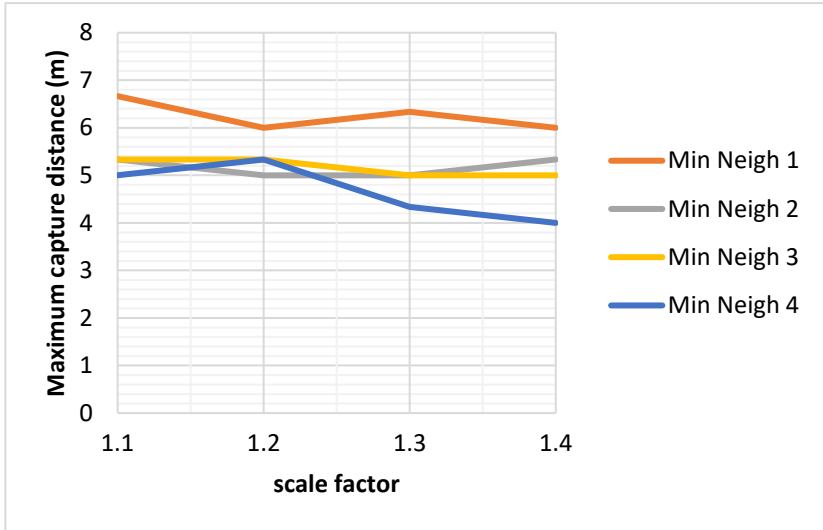

Figure 9: Capture distance against scale factor with constant minimum neighbour (static) for face identification

However at higher min neighbour (4) as seen in Figure 9 resulted in a higher value of standard deviation at 0.6m. It can be noticed that from the same graph, the trend indicates that the maximum capture range decreases as scale factor increase. This difference is apparent due to the combination of high min neighbour with scaling factor. High min neighbour indicates that the system is now required to have a higher number of positive matches for the detected image for it to be considered a positive identification. This increased number of positive matches becomes harder to achive as the number of potential iterations of said images decreases as the subject moves further from the camera and thus reducing the size and subsequently detail of the object. This decrease in possible image iterations and the reduction of frequency of which images are sent for identification culmilates and results in this apparent drop in performance of the recognition system in terms of the range of capture.
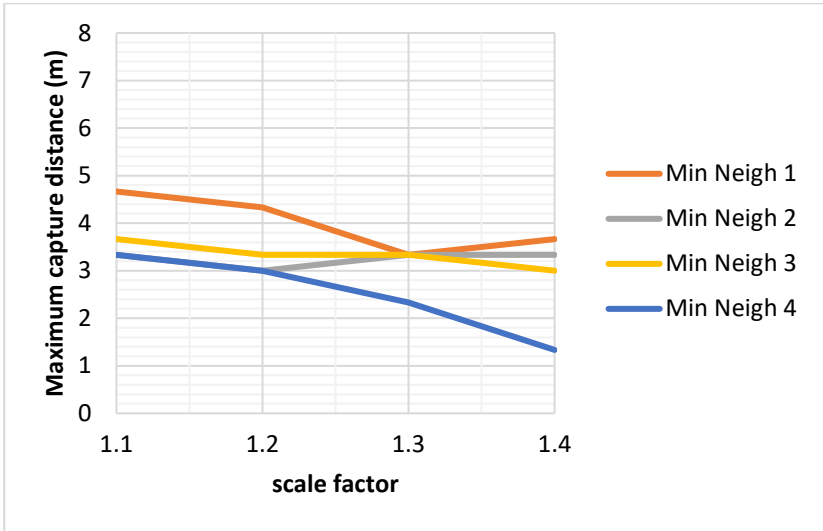
Figure 10: Capture distance against scale factor with constant minimum
neighbour (static) for face recognition.

The results for face recognition mirrors that of face identification at low minimum neighbour (1-3) which is to say that there is no significant observable impact between varying scale factor and the performance in terms of range of capture. While there is a general drop in maximum captured distance when varying the scaling factor from 1.1 to 1.4, the actual drop is small as seen by the small standard variance which ranges from 0.2m to 0.5m. Similarly to identification as well, at minimum neighbour 4, there seems to be a more prominent effect when varying the scaling factor as the standard deviation increased from an average of 0.38m to 0.88m. From comparing the graph side by side, it is clear that face recognition experience a performance drop in terms of maximum capture difference dropping from 6.33m average in face identification to 4.66m average in face recognition and this is expected as face recognition requires more information compared to face identification for it to make a positive claim.
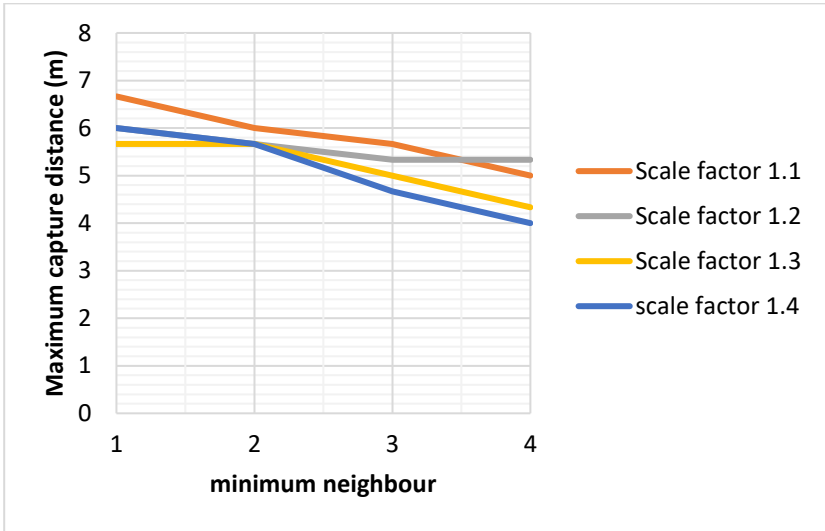
Figure 11: Capture distance against minimum neighbour with constant scale factor (static) for face identification
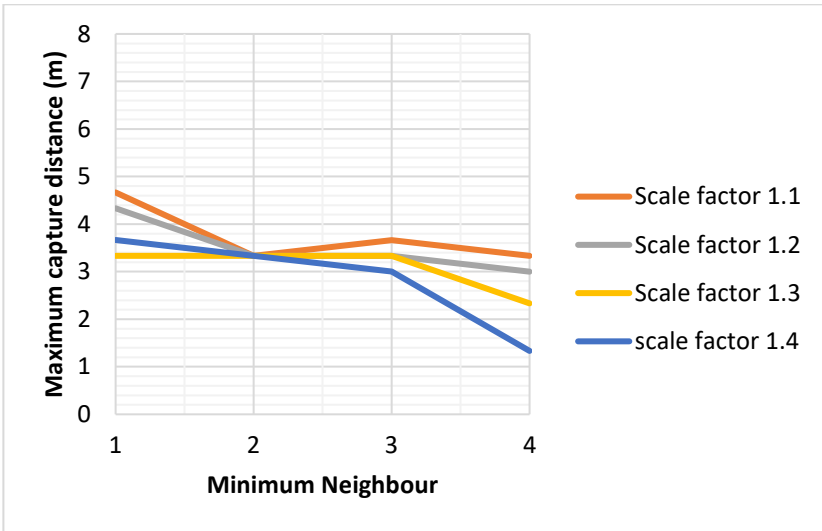

Figure 12:Capture distance against minimum neighbour with constant scale factor (static) for face recognition

However, when comparing the performance of face recognition and identification via varying the minimum neighbour to a constant scaling factor instead, it can be seen that the difference becomes more prominent. Looking at the graphs obtain in Figure 11, it should be noted that there is a clear drop in performance when comparing the results at the lowest minimum neighbour to the highest minimum neighbour and this is further supported by the higher values of the average standard deviation of 0.64m compared to the previous at 0.32m. The results obtained for face identification is again similar for face recognition as well where a clear drop in performance can be seen when the minimum neighbour is increased from 1 to 4 while the scale factor maintains at 1.1 to 1.4 as seen in Figure 12 which also gives us a higher standard deviation of 0.68m compared to 0.508m for when minimum neighbours are constant.

The reason for this apparent difference is due to what minimum neighbour is. The goal of min neighbour is to remove the possibility of a false identification which occurs when the system detects a face but wrongly identifies it as another person. To solve this, we made it such that the system would take multiple iteration of image of the same person (neighbours) and each of those image will be compared with the database for a positive match where if the threshold of positive matches are reached (min neighbour) then a positive identification is declared. This however becomes an issue when the object is further away and the subject in the image shrink due to perspective. The shrinkage in size and detail would result in the system not being able to take the multiple iteration of images it needs to make a positive identification if we set the number of min neighbour to be high and thus why at high values of min neighbour, the performance in terms of distance capture starts to drop significantly.

As a conclusion, smaller scaling factors (high refresh rate) and minimum neighbours (small number of iterations required for positive identification) seems to have the best performance for a static environment. When looking into changing the value, scaling factor has a smaller consequences towards the performance of the face recognition and identification program as per compared to changing minimum neighbours which can be observe from the higher standard deviations of changing minimum neighbours compared to changing scaling factor.

Effects Of Speed On The Performance Of Face Recognition & Identification

Firstly, it can be seen that unlike the results in the static experiment, when the system is mobile at 60% duty cycle ($2.2ms^{-1}$) the performance has a significant drop when varying the scaling factor for face identification as seen in figure 13. We can see that the average standard deviation is 0.622m which in turn indicates that motion has a negative impact on the scaling factor as there is a greater deviation due to the increase of scale factor from 0.32m (static) to 0.622m (60% duty cycle). This visible difference between static and non static when it comes to the effect of scaling factor is expected. Higher scaling factor

implies a higher duration between images being sent for processing. This means, higher scaling factor is less taxing on the system in terms of processing as it would imply that it is processing less images per minute. However, this also implies that there would be more frames that would be lost due to the longer delay between sending images for processing. This lost frames while unimportant in a static detection as the subject remains static and in frame from start to end, in a moving situation, the subject may have entered and exited the frame in varying conditions of capture (blue, no blur). This difference is why the effect of scale factor becomes evident in a dynamic environment when contrast with the results in a static environment.
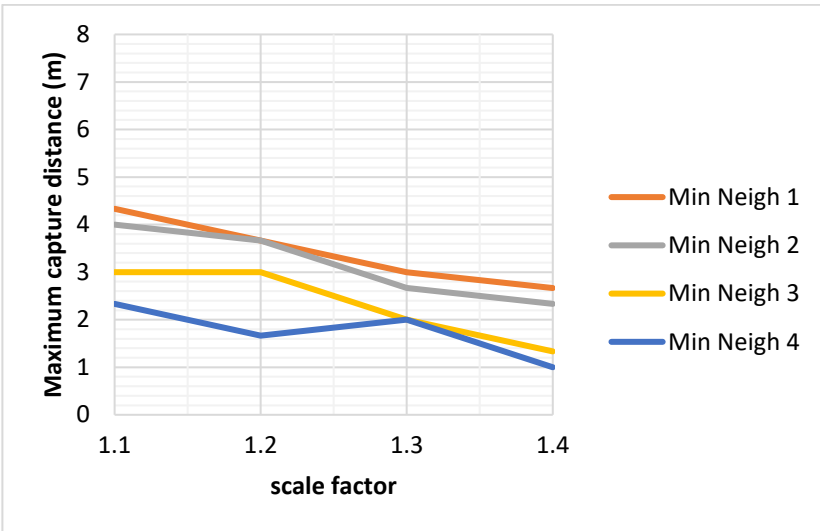

Figure 13: Capture distance against scale factor with constant minimum
neighbour at 60% duty cycle for face identification

The results for face recognition shows similar results to that of identification where the effective range for constant minimum neighbours 1 and 2 are maintained at 2m which is the average distance required for the person to be in the frame for image recognition. At minimum neighbour 3 and 4, recognition fails all together at scale factor 1.3 and 1.4 whereas partially failing at 1.1 and 1.2 hence deriving the average capture distance of 1.333m and 0.666m at 1.1 and 1.2 while 0m at 1.3 and 1.4.
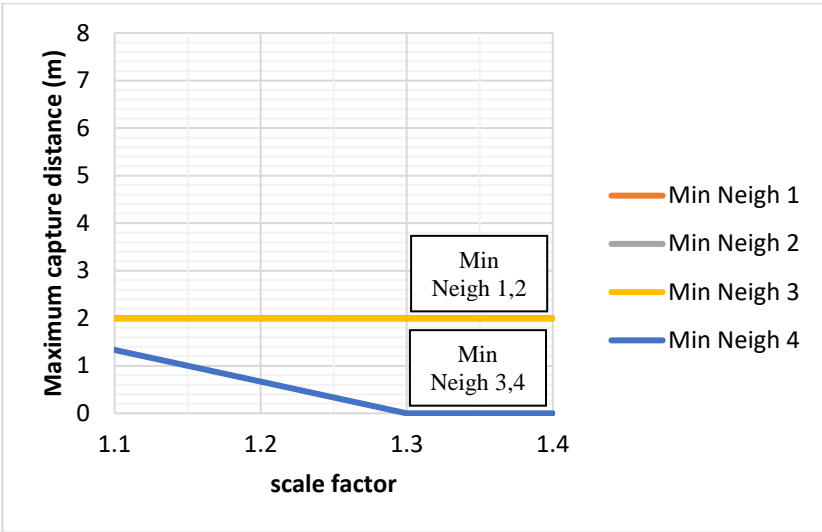
Figure 14: Capture distance against scale factor with constant minimum
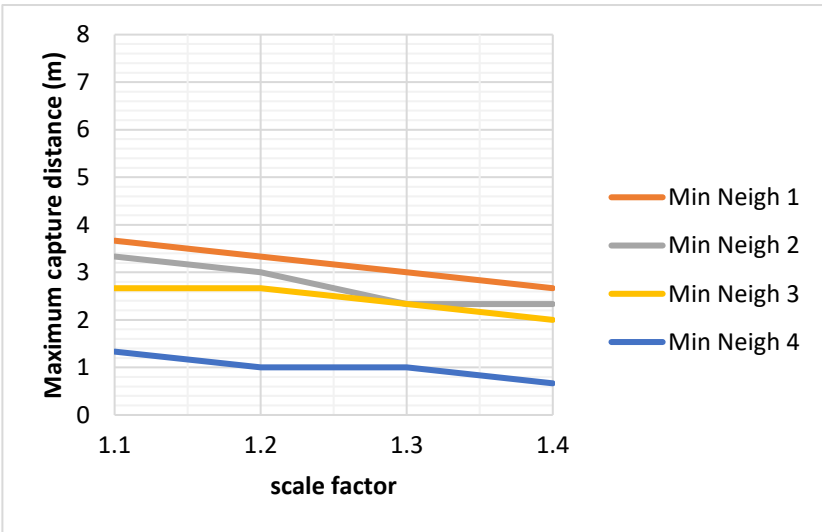neighbour at 60% duty cycle for face recognition.

Figure 15: Capture distance against scale factor with constant minimum
neighbour at 65% duty cycle for face identification.

As a conclusion, it can be seen that the performance in the terms of range of recognition and identification has a clear drop from a maximum range of 6.66m (identification) and 4.66m (recognition) as seen in figure 9 and figure 10 to 4.33m (identification) and 2m (recognition) which can be seen in figure 13 and figure 14 when the robot is moving with duty cycle of 60% which is a 37.5% and 41% drop in performance in both cases. While the difference between identification and recognition is apparent, the difference between static and mobile is predicted. The reason there is a drop in performance between static and mobile can be attributed to motion blurring, which is the effect of images being distorted when velocity is involve. This transmorgified images affect the possibility of a positive identification and recognition and thus why this drop in performance exist and is predicted.

It is worth noting that at 65% duty cycle ($2.4ms^{-1}$), the experiment for distance captured was done for both face recognition and identification however for face recognition the system failed to identify any faces through the experiment. This is thus why only data from face identification was obtained and compared with. This again might be due to the effects of motion blur where an image instance starts to distorts as it is perceived with higher velocities and combined with the higher degree of data required for recognition would be sufficient to explain why recognition failed at 65% PWM.

When we look at the performance of face identification at 65% PWM ($2.4\ ms^{-1}$), the 1st thing we can note is that the maximum distance dropped again from 4.33m at 60% PWM 1.8 ($2.2ms^{-1}$) to now 3.33m which is a 24% performance drop. At low minimum neighbour (1 to 3), the system is still capable of capturing all faces in the image instance however at higher minimum neighbour(4), there are cases where capture fails all together hence giving us an average result of less than 2m as seen in the Figure 15. At higher PWM value (70% and above), face identification fails all together. As theorised in the previous paragraph, this might be due to the effects of motion blur where at 70% PWM ($2.6ms^{-1}$) the blur mitigates too much of the required information for it to be make a positive assesment.

Lastly, we also recorded the time taken for identification as well as recognition in a dynamic environment. This was done by putting a timer at the start of the the dynamic experiment and the timer will stop when the face is identified or recognised. The experiment was done at the first run where the minimum neighbour was set to a constant 1 and the results can be seen in Figure 16. It can be seen that identification occurs faster compared to recognition as an example for subject 1 where identification took 78.33ms whereas recognition took 103ms. It can also be observed that as scaling factor increases the time taken for a positive recognition or identification drops.
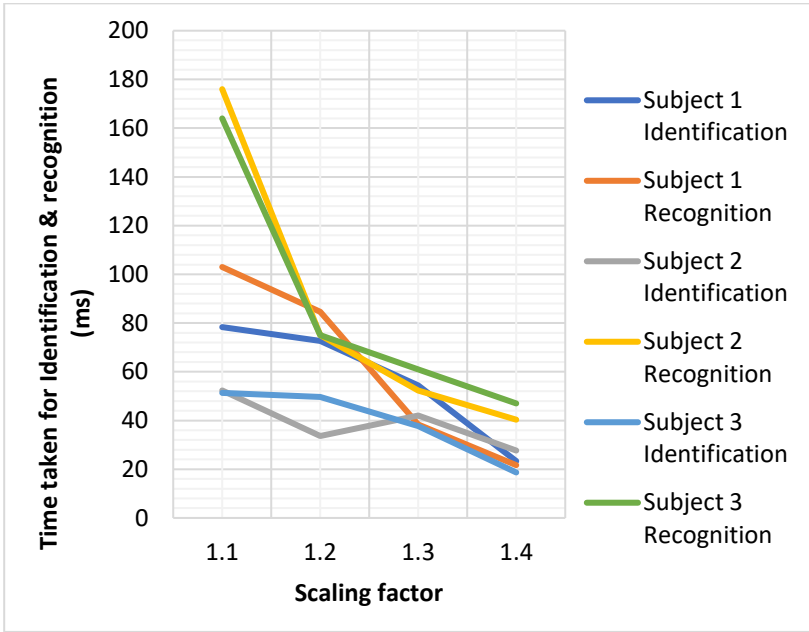
Figure 16: Chart showing Time taken for subject to be identified and recognized by device on static environment under effects of varying scaling factor.

Table 1: Table summraizing the difference in performance in terms of range of capture (m) when varying the speed (ms^{-1}) of the mobile robot.

Duty Cycle	Static	Mobile		
	0% ($0\ ms^{-1}$)	60% ($2.2\ ms^{-1}$)	65% ($2.4\ ms^{-1}$)	70% ($2.6\ ms^{-1}$)
Maximum (average) range of capture for identification	6.66m	4.33m	3.33m	0
Maximum (average) range of capture for recognition	4.66m	2.00m	0	0

This might be due to the fact that scaling factor is number of frames the system would skip before process where scaling factor of 1.1 means every frame is processed and scaling factor of 1.4 means for every 4 frame that passes the system process 1 frame thus it can be assumed that because it skips through more frames at higher setting, it is capable of acessing the important frames where data is sufficient faster compared to lower scaling factor setting hence why it takes less time. This however comes with the caviat of the possibility of it missing out on identification all together as while it is capable of reaching the important frames faster by skiping through a few frames, it is also possible that it skips through the important frame and hence why when cross referencing this results with the previous results, higher scaling factor always results in a shorter effective range.

Conclusion

With this, we have manage to implement a working face recognition system on a mobile robot environment as well as test said face recognition systems performance in the mobile robot environment in terms of its range of capture as well as speed of capture and came to a conclusion that there is a clear drop in performance when comparing performance of static and dynamic. From the test it can be summarized that the range of capture is shorter for face recognition (5m maximum) compared to face identification (8m maximum). Besides that when min neighbour parameter is constant, the effects of varying scaling factor affects the range of capture minimally as the results are almost constant with the exception at higher minimum value range (4) where it seems that the scaling factor affects the capture range negatively. It is also worth noting that when the scaling factor is constant, increasing min neighbour will decrease the range of capture for the device. Finally the Optimum operation for the system to work with the integrated face recognition program was determined to be at 60% duty cycle and the longest range the robot is able to detect is if the robot were to halt before starting face recognition procedure, maximum distance for face identification can be obtained with the minimum neighbour set to 1 and scaling factor set to 1 which will give a maximum distance 5m away while minimum distance the robot has to be away from the subject is 2m which is a 37.5% drop in performance when compared to its performance when the robot is in static condition whereas for face recognition, the maximum distance for face identification is obtained when parameters were set at minimum neighbour 1 and scaling factor 1.1 giving the maximum distance of 4m at maximum and 2m at minimum which is a 41% drop in performance.

Acknowledgement

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